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(54) Method and apparatus for diagnostic testing

Verfahren und Gerät zur Diagnoseprüfung

Procédé et appareil de test pour diagnostic

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D cription

FIELD OF THE INVENTION

The present invention relates generally to diagnostic testing, and more particularly to methods and apparatus for diagnostic testing using evidential reasoning and for determining when sufficient information has been collected to make a valid diagnosis.

BACKGROUND OF THE INVENTION

The assignee of the present invention has previously developed a portable interactive diagnostic tester for fault isolation in complex electromechanical systems called POINTER. POINTER utilizes a model-based, matrix-implemented inferential reasoning method of diagnostic analysis. The diagnostic model is created using the STAMP (System T stability and Maintenance Program) program also available from the assignee of the present invention, ARINC Research Corporation. STAMP is an interactive modeling tool designed to permit analysis of the testability of a system and generation of static fault isolation strategies. STAMP assumes that the system design is known, tests can be specified that measure the goodness and badness of system elements, and sequences of test outcomes can be used to localize or isolate failed system elements. The STAMP diagnostic model describes the flow of information through a system to be diagnosed. The information flow is represented as a set of diagnostic tests (information sources), a set of diagnoses (conclusions to be drawn), and a set of logical relationships between the tests and the conclusions. In addition, the model includes parameters for weighting a test selection optimization process, grouping tests and conclusions, and specifying types of tests to be performed (e.g. functional tests, conditional tests, or asymmetric tests). Under the STAMP methodology, an assumption is made that only one fault exists or that specific multiple faults can be specified and treated as a single fault, and thus that only one conclusion is true for any one diagnostic analysis. (If th system under test actually has multiple faults, they can usually be successively isolated by repeating the diagnostic analysis, unless a "hidden" failure causes the failure which is isolated or a multiple failure looks like an independent single failure.) Evidence from an individual test flows to a set or sets of diagnostic conclusions as either support or denial evidence in accordance with the defined logical relationships. That is, a logical proposition consisting of a set of dependency, or support, functions is established or defined which identifies the conclusions related to a given test and allocates the evidence generated by a test measurement to the set of related conclusions. An example of a higher-order proposition relating a test t_5 to a set of conclusions c_1, c_2, ...c_n is:

If (t_5) then c_1 or c_2 or ....c_n implication

If ($\sim c_1$ and $\sim c_2$ and $\sim$....c_n) then $\sim t_5$ negation

If ($\sim t_5$) then $\sim c_1$ and $\sim c_2$ and ....$\sim c_n$ symmetry

Each unique test has two different support functions, one for each type of evidence (support or denial). There is thus a set of conclusions that are supported and a set of conclusions that are denied by a given test outcome. That is, every conclusion in the model is supported or denied by each test outcome. A test supports a conclusion when the test outcome is consistent with a conclusion value of true. A test denies a conclusion when its outcome is not consistent with a conclusion value of true. In addition, component-to-component dependencies in the system are not modelled, and thus an assumption is made that the evidence for a given conclusion is determined solely by the tests that are related to it, not by other conclusions that may resemble its component parts.

The test measurement results are evaluated and specified as indicating that the tested system element is "Good, " "Bad" or "Unknown" (results not available). A Bad test outcome is equated to be a logically True value of the proposition that corresponds to the test; and a Good test outcome equates to a logically False value of the corresponding test proposition. In the example given above, testing would evaluate the outcome of t_5, and then the truth or falsity of other propositions and conclusions are inferred using the applicable set of support functions. Thus, the STAMP process can be generally described as solving a set membership problem. If a given test is Bad, it implies one of n higher-order causes. If another test is Good, it implies that all of the potential causes of its being Bad are not possible conclusions, so that the complementary set (all potential causes that are still possible) is possible. STAMP operates to ascertain the intersections of the possible conclusion sets.

The STAMP paradigm has proven successful in solving a large number of testability and fault-isolation problems. However, many important problem domains involve uncertainty in both the statements of relation between tests and conclusions and the interpretation of the test measurements. For example, the model assumes that the relationships between th information sources and the diagnostic conclusions are clearly discernible, well defined, and unambiguous. It may not be possible, though, to establish a model which is both accurate and complete, i.e., a mod l in which each conclusion is properly relat d to each t st result, and all of the conclusions which should b related to a test result are specified. Further, the test information may be ambiguous, difficult to interpret, or the user doing the testing and interpreting may have inadequate skill levels to produce reliable test results. Thus, an indicator is ne ded which measur s

how well the modelled relations are fitting the problem to which they are being applied. A number of differ nt approaches have been developed in the artificial intelligence field to deal with the unc rtainty created by these problems. Generally referred to as "reasoning under uncertainty," exampl s of such approaches include th use of c rtainty factors, probabilistic reasoning and weighted causal n tworks. In addition, there are various logics that take into account aspects of uncertainty such as predicate calculus, multi-valued logics, modal logics, non-monotonic reasoning, intuitional logic, truth maintenance, "fuzzy" logic, and Dempster-Shafer evidential reasoning.

However, it is difficult in general to integrate reasoning under unc rtainty concepts with the massive structure and processes associated with a complex, matriximplemented inferential reasoning process like STAMP. Further, although the Dempster-Shafer evidential reasoning approach is well adapted for use in an inferential diagnostic process like STAMP, even this approach to dealing with uncertainty creates a number of serious problems. The Dempster-Shafer technique is flawed in the way it handles total uncertainty. If any test is performed that provides any evidence in support of some conclusion, then uncertainty is reduced--even in the event of a conflict with known information. Ultimately, as further testing is conducted, uncertainty disappears altogether, independent of the test results. Also, applying uncertainty calculations to an inferential system makes the criteria for determining when a diagnostic conclusion may be properly drawn unclear. There is thus a need to determine at what point enough information has been gathered to declare a valid diagnosis, or, in the context of fault isolation, to determine the point at which additional testing is providing minimal useful new information.

Examples of commonly used diagnostic approaches include protocol or decision tree based systems and simulation models; and so called "intelligent" systems such as rule-based expert systems as discussed below.

Shortliffe, E.H. Computer Based Medical Consultations: MYCIN, American Elsevier, New York, 1976.

The first "successful" artificial intelligence application was the MYCIN system developed by Edward Shortliffe at Stanford University. This book was based on Shortliffe's Ph.D. Thesis and describes the use of heuristic rules, backward chaining, and an uncertainty mechanism called "certainty factors" as applied to the problem of diagnosing infectious diseases. The MYCIN system was specifically designed to serve as a decision aid for physicians and physician assistants in the diagnostic process. This system was completely passive and gave no indications of whether more testing was required to make a diagnosis. Rather, only confidence levels were provided with recommended diagnoses and treatments.

Davis, R., "Diagnostic Reasoning Based on Structure," Artificial Intelligence, Vol. 32, pp. 97-130, 1987.

In an attempt to move from the medical domain to the electronics domain, Randall Davis developed a model-based approach to diagnosis focusing on structural and behavioral characteristics of the system being tested. The models used structure to define signal flow through the circuit and behaviour to reason about responses to tests. Davis' model-based approach was also passive and included no mechanism for reasoning under uncertainty. Later work on the model applied entropy-based search to optimize testing and moved the approach from passive to active, but to our knowledge, uncertainty was still left out, Consequently, termination was deterministic, meaning it was based on applying test results to sets of hypotheses until the smallest set that could explain the test results was obtained.

Pipitone, F., "The FIS Electronics Troubleshooting system," IEE Computer, pp. 68-75, 1986.

While working at the Naval Research Laboratory (NRL), Frank Pipitone developed a model-based diagnostic system (the Fault Isolation System -FIS) which was based strictly on structural characteristics of electronic systems. These models are called "dependency models" in the diagnostics literature. The approach was heavily influenced by Davis, but did not include the behavioral knowledge. Further, Pipitone added probabilistic reasoning to the inference process. FIS was an active diagnostic system (i.e. test choice was optimized), but termination was based on testing with certain outcomes as in Davis' approach. In other words, the uncertainty of the answer had no bearing on whether or not FIS would provide an answer, thus degrading the accuracy in the answer.

Allred, Lloyd, "Neural Networks in Automatic Testing of Diode Protection circuits," AUTOTESTCON '89, pp. 181-186.

Neural networks are being applied in increasing frequency to the problem of electronic system diagnosis. This paper by Lloyd Allred provides an example of one application of neural networks for circuit diagnosis as applied to Zener diodes. The described approach involves extracting relevant features from the performance of the diode and using these features to train a neural network. The neural network was based on the architecture of a self-organizing feature map in which feature values are grouped into cells bas d on distance. The cells were th n labelled with fault

identifiers so that when a c ll fired, the corresponding fault was identified. Cell sizes were adjust d through training so that each cell only identified a single fault. The approach described yields a network that is highly specific, system sp cific, and test specific. To be used for testing other units, a new network would ne d to be constructed. This, in fact, is typical of neural network applications for diagnosis.

Examples of known methods which can be used to determine levels of certainty (or "pseudo" probabilities) hav be n cited hereinabove, and includ the following:

McLeish, M., "A Note on Probabilistic Logic," AAAI-88, pp. 215-219, 1988

The question of how one applies probabilistic logic to reasoning systems is addressed in this paper. The question addressed is not specific to diagnostics but concerns whether two forms of probabilistic reasoning (namely maximum ntropy and projection) yield the same result. The benefit of the article is on analysis of reasoning performance to determine validity of the underlying mathematics. It addresses neither efficiency of reasoning nor termination criteria.

Zadeh, L., "Fuzzy logic," IEEE Computer, pp. 83-93, April 1988

Lotfi Zadeh defined a new method of reasoning under uncertainty that he called "Fuzzy Logic." Fuzzy logic, as defined in this paper, is based on the notion of a fuzzy set. Rather than declaring an element to be a member of some set, the mathematics allows a "level" of membership to be associated with the element. Fuzzy logic then consists of methods for combining fuzzy membership values to determine, given multiple pieces of evidence, whether or not some set is characterized by the data.

Shafer, G., A Mathematical Theory of Evidence, Princeton University Press, pp. 35-73, 1976

Believing Bayesian probability theory was powerful but too unwieldy to apply in practice, Shafer devised a modification to Bayesian inference in which he analyzed available evidence to determine levels of belief and denial in a hypothesis. Shafer's theory of evidence provided a means for determining belief intervals for the hypotheses rather than specifying a single probability value. Shafer believed single probability values were too difficult to interpret because they did not provide sufficient information about the reasoning process. This work was not explicitly applied to diagnosis; however, its widest application was in traditional classification tasks (of which diagnosis is an example). The mathematics did not include methods for optimization or termination but considered all available evidence.

Dempster, A.P., "A Generalization of Bayesian Inference," Journal of the Royal Statistical Society, Series 8, pp. 205-247, 1968

Dempster extended the work by Shafer to provide a method for combining evidence from multiple sources. In particular, Dempster defined a "rule of combinations" that permitted an iterative analysis of evidence. The resulting reasoning mechanism is now referred to as "Dempster-Shafer theory" and forms the basis of many reasoning systems most notably sensor fusion systems. Again, Dempster assumed the availability of the needed evidence and did not focus on optimization for evidence selection or termination of the reasoning process.

The rule-based expert system is perhaps the most common of the "intelligent" diagnostic systems. Experts are interviewed to determine how they diagnose, and rules are written to describe the process. Uncertainty is most frequently handled using probabilistic inference or certainty factors.

The objects of the invention are achieved by the apparatus as set forth in claim 1. The dependent claims are directed to preferred embodiments of the invention.

In accordance with the present invention there is provided automatic test data evaluation apparatus for use in a diagnostic tester that declares a diagnosis on the basis of localisation or isolation of failed system elements of a system having a defined number of functional elements, said apparatus comprising:

means for selecting the next test to be performed on the system to be tested;
means for generating the corresponding test data and supplying them to the system to be tested;
means for sensing and collecting predetermined system operating parameters;
evaluating means, responsive to at least one inputted test signal corresponding to test data S_T relating to at least one predetermin d parameter of the system, for producing using a probabilistic evidential reasoning m thod:
first and second candidate signals corresponding respectively to first and second possible diagnoses of the condition of th system respectively having the first and second highest levels of certainty of being valid, and
first and second certainty signals corresponding respectively to values of said first and second highest levels of certainty; and

characterized by testing sufficiency means, responsiv to said first and second c rtainty signals, for producing an output signal indicative of whether sufficient test data has been evaluated to declare a diagnosis, said testing sufficiency means comprising a n ural network having an output nod and at least thr input nodes resp ctiv ly r c iving said first and second certainty signals and a predetermined bias signal as an input, said input nodes having weight d outputs, the output weights corresponding to a model of expert data correlating combinations of certainty signals with at least one expert opinion regarding th ability to declare a diagnosis on the basis of ach combination of c rtainty signal values.

The present invention provides improved diagnostic testing methods and apparatus which deal with uncertainty and overcome the deficiencies of conventional approaches.

The present invention also provides improved evidential reasoning based diagnostic testing methods and apparatus which overcome the limitations of the Dempster-Shafer approach.

The present invention also provides methods and apparatus for determining the sufficiency of testing in diagnostic testing methods and apparatus which deal with uncertainty.

The present invention also provides a neural network method and apparatus for determining the sufficiency of testing in diagnostic testing methods and apparatus dealing with uncertainty wherein the neural network can be trained to have generic application to different diagnostic models and different systems.

Typically said evaluating means also produces an uncertainty signal corresponding to a measure of the uncertainty that the evaluated at least one test signal can be validly evaluated; and

said neural network comprises:

a set of first, second, third and fourth input nodes each having first, second and third outputs weighted by a predetermined fixed weight, said first and second input nodes respectively receiving said first and second certainty signals as an input, said third input node receiving said uncertainty signal, and said fourth input node receiving said predetermined bias signal;

a set of first, second, third and fourth intermediate nodes each having an output weighted by a predetermined fixed weight, and said first intermediate node receiving the sum of the first weighted outputs of said input nodes as an input, said second intermediate node receiving the same of the second weighted outputs of said input nodes as an input, said third intermediate node receiving the same of the third weighted outputs of said input nodes as an input, and said fourth intermediate node receiving said predetermined bias signal; and

an output node, responsive to the sum of said weighted outputs of said intermediate nodes, for producing said output signal, the output weights of said input and intermediate nodes corresponding to a model of expert data correlating combinations of certainty and uncertainty signal values with at least one expert opinion regarding the ability to declare a diagnosis on the basis of each combination of certainty and uncertainty signal values, said testing sufficiency means thereby also evaluating said uncertainty signal to produce said output signal.

Typically said evaluating means also produces a signal S_N corresponding to a measure of the level of certainty that a diagnosis not corresponding to said first or second candidate signals or to said uncertainty signal is a valid diagnosis; and

said testing sufficiency means also evaluates said signal S_N to produce said output signal.

The diagnostic tester typically further comprises means for storing a model of predetermined information flow relationships within the system under test; means for associating the test signals with sets of possible causes in accordance with the model, and for ascertaining the intersections of the sets of possible causes for combinations of test signals, the candidate signals being derived from the intersections; and means for determining for each candidate signal a measure of the level of certainty that it represents a valid diagnosis.

Typically the diagnostic tester further comprises means for defining a plurality of conclusions corresponding to possible diagnoses of the system; means for assigning a confidence value to each successively inputted test signal; means for calculating the support and denial for each conclusion based on the confidence value of the currently inputted test signal; means for determining if the currently inputted test signal conflicts with a then selected set of said conclusions corresponding to candidate signals; means for obtaining a measure of internal conflict based on accumulated total support values and the current test signal support values for all of the conclusions; means for computing the present value of the uncertainty signal based on the number of test signals evaluated, if the present test signal is not a conflict; and based on the number of test signals evaluated and the number of conflicts, if the present test signal is a conflict; means for computing a new total support value for each conclusion based on the old support value, the present test signal support value and confidence value, an old uncertainty value, and the measure of int rnal conflict; means for computing a new uncertainty value based on the old uncertainty valu , the present test signal confidenc value and the measure of internal conflict; means for normalizing the total support value for each conclusion based on the old total support value, and the present uncertainty signal value; means for computing a new total denial for ach conclusion based on an old total denial and the present t st signal denial value; m ans for computing th present

plausibility for each conclusion based on the present total denial and the number of t st signals evaluated; means for selecting the current set of candidate signals based on the present total support and the plausibility for each conclusion.

While a pur ly inf r ntial form of STAMP provides a very good method for optimizing the choice of the next test to maximize the efficiency of the diagnostic process, this method breaks down when an vidential r asoning approach is adopt d. Heretofore, the problem of test selection has not b en addressed in the field of evidence combination. Second, the process of identifying the conclusions, observations and relationships that should be involved in a given evidential diagnostic process is much more difficult than with a strictly inferential process.

Typically the diagnostic tester further comprises an arrangement for testing a system according to a set of defined relationships between a plurality of sources for providing information about the system and a plurality of conclusions about the nature or condition of the system, said tester comprising first means for successively selecting an information source from among the plurality of information sources for interrogation according to the relative amount of information provided by each information source until all of the information sources have been selected or the information which would be provided thereby has been determined;

second means for successively further selecting an information source from among the plurality of information sources for interrogation according to which information source will increase the level of certainty that a selected candidate conclusion constitutes a valid diagnosis of the system being tested.

These and other features and advantages of the present invention are disclosed in or apparent from the following detailed description of preferred embodiments.

The preferred embodiments are described with reference to the accompanying drawings, wherein like features have been designated with like reference numbers, and wherein:

Fig. 1 is a diagrammatic view of a first embodiment of a diagnostic tester according to the present invention.

Fig. 2 is a schematic block diagram of the basic functional components of the diagnostic tester of Fig. 1.

Fig. 3 is a schematic block diagram of the control and diagnostic analysis CPU of Fig. 2.

Fig. 4 is a diagrammatic view of a second embodiment of diagnostic tester according to the present invention.

Fig. 5 is a schematic block diagram of an automatic system tester incorporating diagnostic testing apparatus in accordance with the present invention.

Fig. 6 is a schematic block diagram of a system controller incorporating diagnostic testing apparatus in accordance with the present invention.

Fig. 7 is a schematic block diagram of the controller and diagnostic test signal evaluating sections of a diagnostic tester according to the present invention.

Fig. 8 is a general flow chart of a diagnostic process performed by a diagnostic tester in accordance with the present invention.

Fig. 9 is general flow chart of a preferred diagnostic process performed by a diagnostic tester in accordance with the present invention.

Fig. 10 is a more detailed flow chart of a preferred test selection process performed by a diagnostic tester in accordance with the present invention.

Fig. 11 is a more detailed flow chart of a preferred evidential reasoning based process performed by a diagnostic tester in accordance with the present invention for selecting a conclusion from among a plurality of conclusions as a diagnosis based on inputted test signals.

Fig. 12 is a diagrammatic illustration of a first embodiment of a neural network in accordance with the present invention for determining the sufficiency of the testing by a diagnostic tester.

Fig. 13 is a diagrammatic illustration of a second embodiment of a neural network in accordance with the present invention for determining the sufficiency of the testing by a diagnostic tester.

DETAILED DESCRIPTION OF PREFERRED EMBODIMENTS

Referring to Figs 1-6, the diagnostic testing methods and apparatus of the present invention advantageously are incorporated in diagnostic testers which are adapted to receive test data input from an operator or from other sources (Figs. 1-4); in automatic system testers which are adapted to automatically both test a system and analyze the test results (Fig. 5); or in automatic system controllers which sense the condition of the controlled system and control the operation of the system in response thereto (Fig. 6). The present invention may also readily be embedded within systems having self-diagnosis capabilities as part of the self diagnosis architecture. As shown in Figs. 1-3, one form of manual input diagnostic tester which is portable has a separate housing 11 which contains the tester components; a display 12 mounted in housing 11 for displaying t st results, diagnoses, user prompts and similar types of information; a keyboard ar a 13 comprising a plurality of data entry keys 14 and a plurality of command keys 15 for ent ring test data and user commands to control the op ration of the tester; conventional signal g n rating circuitry 16 responsive to actuation of keys 14 and 15 for generating digital electrical test and command signals, respectively, corresponding to the test data and commands enter d by the operator; and a control and diagnostic analysis central processing unit

(CPU) 17 for controlling the operation of the tester and performing the diagnostic analysis routin s stored therein. As is conventional, CPU 17 comprises a processor 17a for performing control and analysis operations under control of an op rating program stored in a read-only memory (ROM) 17b, and a further data m mory 17c for storing inputted test and command signal data and the data generated in th course of operation of processor 17a.

Referring to Fig. 4, another form of a diagnostic tester in accordance with th present invention comprises a conventional general purpose or dedicated computer system 20 comprising a display 22, a CPU 24 programmed to perform diagnostic analysis routines, and an input interface 26 for receiving test data and command signal input. As will be appreciated by those skilled in the art, CPU 24 has the same general functional organization as CPU 17 shown in Fig. 3. Input interface 26 advantageously comprises a conventional keyboard or other user interface device for generating test data and command signals in response to operator actuation of the device, or a conventional peripheral interface device for receiving test data and command signals from a peripheral source such as a storage memory or system controller; and converting, if appropriate, the test data and command signals to digital signals in a form compatible for processing by CPU 24.

Referring to Fig. 5, an automatic system tester 30 for testing a system A which incorporates a diagnostic tester in accordance with the present invention comprises a controller and diagnostic test signal analyzer 32 for generating control signals to control the operation of tester 30 and for analyzing test signals indicative of the nature or condition of system A which are generated by tester 30; a test generator system 34 for performing predetermined tests on system A responsive to control signals generated by controller/analyzer 32 and for generating the test signals corresponding to the test results; and a display 36 responsive to control signals from controller/analyzer 32 for displaying test information, diagnoses, user prompts and the like.

Referring to Fig. 6, a diagnostic tester in accordance with the present invention is shown incorporated in a system controller 40 controlling the operation of a system A. System controller 40 comprises a sensor/control unit 42 for sensing predetermined system operating parameters and for generating control signals for controlling the operation of system A; and a diagnostic tester 44 for evaluating the sensor data and generating output signals used by sensor/control unit 42 for generating the control signals.

The diagnostic tester of the present invention has broad application in determining the nature or condition of a variety of systems, ranging, for example, from determining faults and malfunctions in electronic or electromechanical systems or manufacturing processes, to selecting the appropriate control response according to the sensed state of a controlled system, to identifying a disease or other abnormal condition in an organism, to identifying objects within a space, to classifying animals or other objects or materials according to a taxonomy or other classification scheme. For the sake of clarity, the diagnostic tester of the present invention will be specifically described hereinbelow in the context of fault diagnosis of complex systems, wherein malfunctioning systems having a plurality of functional components or elements are analyzed to isolate the source of a fault.

Referring to Fig. 7, the basic preferred functional configuration of processor 17a, CPU 24, controller and diagnostic test signal analyzer 32, and the control portion of sensor/control unit 42 and diagnostic tester 44 comprises a controller section 52, a test signal evaluation section 54, and a sufficient testing evaluation section 56. Controller section 52 generates control signals S_{Con} for controlling the associated display 12, 22, 36 and/or test generator 34 and system A.

Test signal evaluating section 54 evaluates inputted test signal data S_T resulting from testing or sensing of some aspect, referred to hereinafter as a parameter, of system A, and produces a plurality of n candidate signals S_C corresponding to n possible diagnoses of, or diagnostic conclusions about the condition of system A, where $n \geq 2$, and each candidate signal S_C has an associated level of certainty of representing a valid diagnosis, that is, a diagnosis having associated therewith an acceptable level of confidence that the diagnosis is correct. Hereinafter, the candidate signals having the first and second highest levels of certainty of being valid are denoted S_{CP1} and S_{CP2}. Test signal evaluating section 54 also produces first and second certainty signals S_{P1} and S_{P2} corresponding respectively to measures or values of the first and second highest levels of certainty associated with candidate signals S_{CP1} and S_{CP2}. Test signal evaluating section 54 also preferably produces uncertainty signals S_U corresponding to a measure of the uncertainty that the evaluated test signals S_T can be validly evaluated to produce a diagnosis.

Sufficient testing evaluating section 56 produces an output signal S_S indicative of whether sufficient test data has been evaluated to declare a diagnosis based on at least the certainty signals S_{P1} and S_{P2}, and preferably also based on uncertainty signal S_U. In addition, test signal evaluating section 54 advantageously also generates an associated signal S_N corresponding to a measure of the level of certainty that a conclusion other than S_{CP1}, S_{CP2} and S_U is the correct diagnosis, and the output signal S_S of sufficient testing evaluating section 56 is also based on signal S_N.

Referring to Fig. 8, in general, the procedure followed to make a system diagnosis in accordance with the present invention comprises the steps of selecting information sources (the diagnostic tests/sensed param ters) to be valuated (step SS1); collecting information via these information sources (performing the selected test/sensing the selected param ter and evaluating the results to produce test data) (step SS2); analyzing the information (test data) coll cted (step SS3); drawing a candidate conclusion or conclusions about the situation examined (generating candidate signals S_C) (step SS4); and determining whether sufficient testing has been conducted to declare one or more of th conclu-

sions as the diagnosis, or to d clare that further t sting is unlikely to establish a diagnosis (Step SS5). If the step SS5 determination is positive, then further testing is terminated and a diagnosis is declared, if appropriate (step SS6). If the step SS5 determination is negative, then the procedure is repeated by returning to step SS1, unless some other termination crit rion is satisfied.

In accordance with the present invention, any conventional method can be used to select the tests to be performed/ parameters to be sensed, and to collect the test data. Similarly, any conv ntional method can be used to analyze the test data and draw candidate conclusions (generate candidate signals S_C) which also provide a measure of the levels of certainty that the various candidate conclusions are valid.

A preferred model-based method of test selection and test data analysis for fault diagnosis of complex systems in accordance with the present invention which employs a modified form of Dempster-Shafter evidential reasoning will now be described. In accordance with this method, the problem of diagnosis is approached as a collection of subproblems:

(1) Modeling: A diagnostic problem is treated as a modeling problem in which available information sources, the desired set of diagnostic conclusions, and their interrelationships are specified.
(2) Optimization: The information sources are selected for consideration in a way that optimizes the diagnostic process according to one or more criteria.
(3) Logical Inference: Test data derived from the information sources is used to draw inferences about other information sources and about the diagnostic conclusions in the model. The inferences are drawn based upon the relationships specified in the model.
(4) Statistical Qualification: Statistics describing the support and plausibility of each diagnostic conclusion in the model are computed based upon the information sources examined, the information collected, and the confidences in the reliability of that information.
(5) Statistical Inference: Statistics generated from collecting information from each information source are combined to determine the total support and plausibility for each diagnostic conclusion in the model.

These statistics are then used to estimate the probabilities that the corresponding conclusions constitute correct diagnoses. The resulting probabilities are then examined in the manner described in more detail hereinafter to determine if sufficient information has been collected to make a confident, valid diagnosis, and if not, whether further test data should be collected. If the determination is positive because sufficient information is deemed to have been collected, then further testing and evaluation are terminated and the diagnosis corresponding to candidate signal S_{CP1} having the highest certainty level of being valid is declared as the diagnosis. Alternatively, if the determination is positive because the uncertainty due to conflict is such that no confident valid diagnosis can be made in the near term, then further testing and evaluation are terminated and the diagnosis which is declared is that corresponding to uncertainty signal S_U, i.e., that a valid diagnosis cannot be made. If the determination is negative because insufficient information has been collected, then further testing and evaluation are conducted until a positive determination is obtained, unless another termination criterion is satisfied. Two such criteria are whether a trend analysis indicates that additional test data collection is not improving the ability to select a conclusion as the fault diagnosis; and whether all information sources have been used a predetermined number of times without a determination being made that sufficient information has been collected. Preferably, the repetition limit varies for each test according to the confidence values (described in more detail hereinafter) assigned to the test. In the preferred embodiment, the standard limit is 4 unless the value of the greater of the Good and Bad base confidences is less than 0.85. Then the limit is reduced as follows:

if $0.75 < \text{Base} \leq 0.85$, then the limit = 3;
if $0.6 < \text{Base} \leq 0.75$, then the limit = 2; and
if $\text{Base} \leq 0.6$, then the limit = 1;

where Base is the greater base confidence value.

A typical fault isolation determination using a diagnostic model generated by the aforementioned STAMP program involves choosing tests, performing the tests, evaluating the results of the tests to assign a value of "Good," "Bad," or "Unknown" to the results, and qualitatively qualifying the "Good" and "Bad" values according to the confidence of the user in the result. (For example, the user can specify that the designated Good/Bad result is certain, somewhat certain, marginal, somewhat uncertain, or uncertain.) The qualifiers are then converted to numerical confidence factors which are used to compute evidential statistics (support and plausibility) for each conclusion provided in the model. The fault diagnosis process will now be described in detail with reference to Figs. 9-13.

THE DIAGNOSTIC MODEL

Referring to Fig. 9, the first step (SS 10), is to define the diagnostic model. Preferably, the diagnostic model us d consists of a description of the flow of information through a system to be diagnosed. Th information flow is represented

as a set of diagnostic tests (information sources), a s t of diagnoses (conclusions to be drawn), and a set of relationships between the tests and the conclusions. In addition, the model preferably includes parameters for weighting the test selection optimization process, grouping tests and conclusions, and specifying types of t sts to be p rformed (e.g. functional tests, conditional tests, or asymmetric tests). The model may be specified as a topological description of a system, the dependency model b tween failure modes and probe tests, a collection of IF...THEN... rules as in a rule-based xpert system, or any other formulation that describes the relationship betwe n information sources and conclusions.

Advantageously, the tool used to develop the model is the aforementioned STAMP program, which is described in the ARINC Research publication, STAMP User's Guide, Tech. Note 213 (March, 1987), by the inventors Sheppard and Simpson herein, and which is hereby incorporated herein by reference. STAMP can be used to develop any model that meets the requirement described in the previous paragraph. The models generated by STAMP permit diagnoses to be performed in a dynamic, context sensitive environment. Diagnostic strategies are computed based on known information; and can be tailored and adapted to changing conditions, such as failing test equipment, or change of emphasis from minimum time to fault isolate to minimum required skill level to fault isolate.

GENERATING THE DIAGNOSTIC SEQUENCE

Once a model has been established (STAMP creates a computer readable file which is loaded into the processor constituting controller and test signal evaluating sections 52 and 54), the user may, optionally, specify a collection of symptoms and initial conditions (such as weighting criteria and groupings).

In order to provide an efficient and dynamic approach to diagnosis, two elements are essential: 1) a method of choosing information sources that result in a conclusion being reached utilizing a minimum amount of some required resource; and 2) a method for inferring information from actions taken by the user in order to adjust the diagnostic system's knowledge of the current state of the problem. The manner in which information sources are selected so as to optimize the diagnostic process in accordance with the present invention will be discussed next. The following discussion assumes that no grouping has been specified, no test outcomes (symptoms) have initially been determined, and a cost weight has been selected for information source selection optimization (i.e., the information source selection is biased in favor of a less expensive source (test) over a more expensive source).

In the preferred embodiment a complete diagnostic sequence is generated in two test selection phases (step SS 20). The first phase (steps 214-226 of Fig. 10) consists of selecting tests based upon the amount of information they provide (and subject to any other selected weighting or grouping criteria). When a diagnostic procedure is first started, all of the tests in the model are available for consideration and all of the possible diagnostic conclusions in the model are still under consideration. If symptom information (or initial conditions) are then loaded by the user, they are used to prune the problem space using the inference meta-rules described below. At this point, some tests are still unknown and some conclusions have no evidence denying that they are possible. The tests that provide the most discriminating information about the candidate conclusion set regardless of the outcome of the individual tests are selected, as described in more detail hereinbelow. Referring to Fig. 9, when the selected test is performed (step SS30) and the results of a test are evaluated to produce test data (step SS40), the test data are processed by an inference engine, to be described hereinafter (step SS60), and another test is chosen in the same fashion as described above. Referring to Fig. 10, this process continues until there are no more tests to choose (i.e. all tests have either been evaluated or their outcomes have been inferred) (step SS210).

Referring still to Fig. 10, the specific process of choosing a test is based on Shannon's Theory of Information. For each test that is available, the amount of information that will be learned if the test passes (i.e., is good) is computed (step SS214). The amount of information learned from a good outcome is taken to be the number of tests that the test depends on plus the test itself. This test passed information value is then multiplied by the test's corresponding "good" "base confidence", a measure of the maximum confidence one can have in a good outcome, to produce a first product value (step SS216).

Then the amount of information that will be learned if the test fails (i.e. is bad) is computed (step SS218). The amount of information learned for a bad outcome is taken to be the number of tests that depend upon the test, plus the number of tests that can be designated "not needed," plus the test itself. A test may be designated as not needed if the test neither depends on nor is depended on by the test under consideration unless designating that test "not needed" creates a new ambiguity within the model. A new ambiguity is created if two or more conclusions that used to have different test dependency sets would have the same test dependency set because a test which is the only differentiator between the conclusions is the t st about to be declared not needed.

Once computed, the test failed information value is then multiplied by the test's corresponding "bad" bas confidence, a measure of the maximum confidence one can have in a bad outcome, to produce a second product value (step SS220). Base confidences are defined by the user for both good and bad test outcomes. The two values do not have to be qual.

Next, the minimum of th first and s cond product valu s is identified for ach test (step SS222). Normalized weight values are then computed and multiplied by the minimums just stored to produce third product values. As with the base confidence values, cost and other dir ct weight valu s aff cting test s lection are also specified by the user (or learned from actual diagnostic experience). Direct weighting of the tests is accepted which is inversely proportional to the informational value of the test, and indirect w ighting of the tests is accept d through weighting of the related conclusions which is directly proportional to the value of th test being weighted. As will be appreciated by those skilled in the art, a direct weight is a weighting factor applied directly to the tests in the model. Examples of direct weights include test time, test cost, or skill level required to test. An indirect weight $W_{Indirect}[j]$ applied to the conclusions in a model are attributed to the tests as follows:

$$W_{Indirect}[j] = \Sigma_i(w_i d_i)/\Sigma_i w_i$$

where

w_i = a user-specified indirect weight associated with conclusion c_i
t_j = a test
d_j = 0; if t_j does not depend on c_i
d_j = 1; if t_j does depend on c_i.

Examples of indirect weights include failure rate, criticality and safety.

It will also be appreciated that when one or more weights are applied to information values in the test selection process, then an emphasis factor may also be associated with any weight which has the effect of increasing the significance of the weight over other weights and/or the information value. In addition, if test groupings have been specified, then three additional test selection features are available. First, time and cost penalties can be applied that affect time and cost weights until a test group is entered (a test within the group is selected). Second, specific sequencing of tests within groups can be defined which overrides normal test selection choices. Third, sequencing of entire test groups can be defined which also override normal test selection choices.

The normalization process results in the weights for a given criterion summing to 1.0. The maximum of the computed third product values is then determined (step SS226). The test with this maximum third product value is selected as the next test to evaluate.

During the first phase of test selection, an optional additional form of test selection advantageously also is provided. In this test selection mode, the user can specify that the selection be based on a hypothesis (discussed in more detail hereinafter) selected by the user. If the user selects a hypothesis, then all choice overrides and modifiers are disabled, and a test is chosen based on the following rules:

1. A test that has a Bad outcome and depends upon the hypothesis and a minimum number of other unknown conclusions.
2. A test that has a Good outcome and does not depend upon the hypothesis, but does depend upon a maximum number of other unknown conclusions.

The first of these rules is preferred over the second.

At the point all of the tests have a value (either given or inferred), as determined in step SS210, the second phase of choosing tests begins. At this point, one or more candidate failures (conclusions) have been identified and are given as a current hypothesis, as described in more detail hereinbelow. The levels of certainty associated with these failure conclusions are processed in the manner described in more detail hereinbelow to determine if enough evidence has been gathered to declare a diagnosis. If a determination is made that more evidence is necessary, and testing should not terminate, then another test needs to be chosen. At this point, rather than selecting a test that maximizes the amount of information about the system, an attempt is made to choose a test that will either separate multiple hypotheses or further support a single hypothesis. The purpose of this test choice process is to identify sources of evidence that will increase the level of certainty that a selected candidate conclusion (i.e. the current leading hypothesis, as defined hereinafter) is indeed the conclusion that should be drawn.

A test is chosen based on the quantity of evidence according to a process which can include up to four evaluation steps. First, if more than one current hypothesis exists (step SS230), then a t st is chos n that splits the top two hypotheses (the two hypotheses with the highest associated levels of certainty) (step SS232). This is done by examining the dependencies and identifying which tests depend on one hypothesis and not the other hypothesis. The test that furnishes the most evidence and meets this criterion is selected (step SS234). If no tests exist that can separate hypotheses, or only one hypothesis exists, then the next evaluation step is performed. (The second and third evaluation

steps attempt to find a test that provides the most support for the leading hypothesis. In both of these steps, it is assumed that a Bad test outcome is being sought.)

In the second evaluation step, if only on hypothesis has been select d, then the tests are valuated to find the test that provid s the most support for th hypothesis (step SS236). Similarly, if there are multipl curr nt hypotheses, and the first step failed to choose a test, the tests are evaluated to find the test that provides the most support for the l ading one of the hypotheses, i.e., the current hypothesis with the highest level of certainty associated therewith. The intent here is to further strengthen the current or leading hypothesis, which should bring the testing sufficiency evaluation process closer to terminating the fault isolation process. Specifically, only the tests that depend upon the current or leading hypothesis are considered. The test that denies the most conclusions other than the current/leading hypothesis is selected at this point (step SS238). To deny a conclusion, the test cannot depend on that conclusion. If no tests exist that support the current or leading hypothesis, then the next evaluation step is performed.

In the third evaluation step, in the event that a test has not been chosen from step 2, then tests that deny the current or leading hypothesis are examined (step SS240). To do this, only the tests that do not depend upon the hypothesis conclusion are considered. The test that supports the most conclusions other than the hypothesis is selected at this point (step SS242). To support a conclusion, the test must depend on that conclusion. If no tests exist that deny the current/leading hypothesis, then some test must be selected, and the last evaluation step is performed.

In the last evaluation step (SS244), in the event that no tests can be chosen that meet any of the above conditions, then the test with the fewest trials is selected just to select some test. If this fails to select a test, then advantageously the user may be offered the opportunity to choose a test. Failing user selection, an end to testing is declared even if the testing sufficiency evaluation otherwise indicates additional testing is appropriate.

INFERRING INFORMATION FROM TESTING

Referring to Fig. 9, once a test is chosen, the next step is to evaluate the test outcome to provide the test data (Good/Bad with associated confidence factor, or Unknown) (steps SS40-50). The diagnostic model is then analyzed using the hybrid inference engine to determine what additional information can be inferred from the new test outcome (step SS60). The inference engine has two parts, one employing logical inference, and one employing statistical inference. The first, logical, part, which is only active during the first phase of fault isolation as described above, computes logical inferences based on the test outcomes according to i) the STAMP model assumption that there is a single fault or a limited number of specified multiple faults to be isolated and hence a single valid diagnostic conclusion; and ii) eight inference meta-rules (wherein a Good/pass outcome is equivalent to "false" in logic and a Bad/fail outcome is equivalent to "true"):

1. IF a test t[j] is unknown, THEN no inference is available except t[j] is unknown.
2a. IF a test t[j] is false, AND test t[j] is not a negative inference test, as defined hereinafter, THEN every test upon which it depends is false.
2b. IF a test t[j] is false, AND test t[j] is not a negative inference test, THEN every conclusion upon which it depends is false.
3a. IF a test t[j] is true, AND test t[j] is not a positive inference test, as defined hereinafter, THEN every test that depends on t[j] is true.
3b. IF a test t[j] is true, AND test t[j] is not a positive inference test, THEN every conclusion upon which t[j] does not depend is false (due to the single conclusion assumption noted hereinabove).
3c. IF a test t[j] is true, AND test t[j] is not a positive inference test, THEN any test t[p] that is currently unknown and is not a dependency of t[j] is not needed, UNLESS declaring t[p] not needed creates a new ambiguity among the conclusions (due also to the single conclusion assumption).
4. IF after rules 1-3 have been evaluated, any t[p] is unknown and depends on all of the unknown conclusions, THEN t[p] is true.
5. IF after rules 1-4 have been evaluated, any t[p] is unknown and depends only on false conclusions, THEN t[p] is false.
6. IF the outcome of test t[j] is linked, as defined hereinafter, to an outcome of t[i], THEN the outcome of t[i] is determined by the linkage, AND rules 1-5 are applied to t[i].
7. IF a test t[j] is true, AND t[j] is a negative inference test, AND t[j] is cross-linked, as defined hereinafter, to a positive inference test t[i], THEN t[i] is true.
8. IF a test is false, AND t[j] is a positive infer nce test, AND t[j] is cross-linked to a n gative inference test t[i], THEN t[i] is false.

For purposes of these tests, a negative inference test is defined to be a test that will result in inference only if it has a true value. If th value of a negative inference test is false, then no inference can be made except the value of the t st.

A positive inference test, on the other hand, is defined to be a t st that will result in inference only if it has a false value. If the value of a positive inference test is true, then no inference can be made except the value of the test. The linkage mentioned in rule 6 refers to the situation in which a test t[j] b ing tru triggers th value of a linked test t[i] being false, and a t st t[j] being false triggers the value of t[i] to be true. The cross linkages mention d in rules 7 and 8 mean that two tests are declared to be asymmetric (i.e. either positive or negative inference), and as such, a false value for a n gative inference test triggers a false value in a linked positive inference test, and a true positive inference test triggers a true value in a linked negative inference test.

It will be appreciated that other sets of inference rules, or other reasoning approaches may also be used to derive information from the test data for use in the diagnostic process.

The second, statistical, part of the inference engine functions throughout the entire diagnostic process (and thus in parallel with the logical part during the first phase of test selection when the inferential part is active). Several statistics based on the evidence gathered are computed that describe the level of certainty for each diagnostic conclusion in the model that it is the correct conclusion. This computation incorporates a method of attributing evidence to conclusions in the model to compute measures of support and plausibility for the conclusions. As is known from Dempster-Shafer theory, there are two measures of the amount of evidence accumulated for a conclusion--"belief" and "plausibility." They are directly related to the evidence provided by tests. Support evidence from a test affects the belief of a conclusion. Belief differs from support in that it represents the total support evidence available for a given conclusion; support is that portion of the evidence from one test that is directed to a given conclusion. The $\text{Support}_{\text{Total}}[c_i]$ value used below is analogous to belief.

Denial evidence affects the plausibility of a conclusion. Just as belief is the accumulation of support, plausibility is the accumulation of denial. However, it has a different sense than denial. Plausibility represents the upper limit on the belief. The relation between belief and plausibility is:

If the belief in a proposition A is equal to Pr(A) (the probability that A is true), the denial of proposition A is equal to the Pr(not A), $0 \le \Pr(\text{not } A)$ and $\Pr(A) + \Pr(\text{not } A) \le 1.0$,
then $\Pr(A) \le 1 - \Pr(\text{not } A)$
or belief ≤ plausibility

Evidence for a proposition is represented by a credibility interval [belief, plausibility]. Each interval is a subinterval of the probability interval [0,1] with the lower bound (the belief) representing the degree to which the evidence supports the hypothesis, and the upper bound (the plausibility) represents the degree to which the evidence fails to refute the hypothesis. Under Dempster-Shafer theory, the difference between belief and plausibility represents the residual ignorance or uncertainty. Under Bayesian theory, the total probability of a proposition and its negation must be one, while under Dempster-Shafer theory, these probabilities do not necessarily sum to 1. The difference is uncertainty. Thus, the support measure quantifies the amount of supporting evidence for a given conclusion and is given by the confidence in the test outcome. Plausibility, on the other hand, provides a measure of the denial of conclusions and is simply one minus the support of all conclusions not supported by the test outcomes. The advantage of a Dempster-Shafer approach to estimating levels of certainty over a Bayesian approach is that prior probabilities do not need to be determined. Rather, the support and plausibility measures are determined solely by testing, the confidences in the test outcomes, and the known relationships between tests and conclusions.

The computations performed by the statistical part of the inference engine are based on a modified version of the Dempster-Shafer evidential reasoning process. This process associates a confidence value with each test outcome in the range of 0.0 ... 1.0. As noted hereinabove, base confidences define maximum confidence values for good and bad outcomes respectively. In addition, the user specifies if qualifiers are to be associated with the good and bad outcomes. If qualifiers are not associated, then the base confidences are selected as default confidence values, e.g., 0.999, which advantageously can be either predetermined independently of the diagnostic model or can be specified for a particular model at the time the model is being developed. If qualifiers are associated, then the user (optionally) lists the appropriate qualifiers in decreasing order of confidence level. Otherwise, default qualifiers, e.g., certain, somewhat certain, marginal, somewhat uncertain, uncertain, are used. Once the qualifiers are associated, good test and bad test confidence values are assigned to the qualifiers as follows:

$$\text{Confidence}[t_k] = \{\tfrac{1}{2}[(N-i)/(N-1)]^{*}\text{Base Confidence}\} + 0.5$$

where

$\text{Confidence}[t_k]$ =	the good/bad confidence value for the good/bad outcome of test t_k
Base Confidenc =	the corresponding good or bad bas confidence assign d to the test
N =	the total number of qualifiers ($N \ge 2$)
i =	the ordinal number of the s lect d qualifier

For example, given the default qualifiers and a good base confidence of 1.0, good t st confidence values would be assigned as follows:

certain	-- 1.0
somewhat certain	-- 0.875
marginal	-- 0.75
somewhat uncertain	-- 0.625
uncertain	-- 0.5

At the outset of the statistical computations, the total accumulated support and denial values for each conclusion, $\text{Support}_{\text{Total}}[c_i]$ and $\text{Denial}_{\text{Total}}[c_i]$, respectively, and the uncertainty signal S_U are each initialized to 0.0; and the plausibility value for each conclusion, Plausibility$[c_i]$, and the Uncertainty value are each initialized to 1.0. If a test outcome is true, then that test outcome supports conclusions upon which it depends and denies conclusions upon which it does not depend. On the other hand, if the test outcome is false, then that test outcome supports conclusions upon which it does not depend and denies conclusions upon which it depends. The amount of support for a given conclusion i by a given test t_k outcome is computed as follows:

$$\text{Support}[c_i] = \text{Confidence}[t_k]/|C|$$

where

C =	set of conclusions supported
|C| =	size of C.
Denial$[c_i]$ =	Confidence$[t_k]$

The above equations apply only for computing support and denial from a single source of evidence. Evidence furnished by multiple information sources are combined using a modified form of Dempster's Rule of Combinations. First a measure of internal conflict K is computed:

$$K = \Sigma_i \Sigma_j (\text{Support}_{\text{Total}}[c_i]^* \ \text{Support}[c_j]; \ i<>j.$$

Next, the number of conflicts is tallied. A conflict occurs when the outcome of a test denies all of the current hypotheses, which hypotheses correspond to candidate signals S_C, and are determined in the manner described hereinbelow.

To determine the current hypothesis, all of the tests must have a value (good, bad, unavailable, or unneeded). At this point in the diagnosis procedure, the first phase of the test selection process has been completed and the second phase has been commenced. Since most users are at least intuitively familiar with probability, preferably the first step in determining the current hypothesis (or hypotheses) is to compute an estimate of the probability that each conclusion is the answer. The evidential support and plausibility statistics for each conclusion are converted to an estimated probability value $S_P[ci]$ (signal S_P) as follows:

$$S_P[c_i] = ½(\text{Support}_{\text{Total}}[c_i] + \text{Plausibility}[c_i]).$$

The estimated probability of the UR, defined hereinafter, is treated as a special case by assuming its estimated probability is strictly the value of Support[U] (the support for the UR calculated as set forth hereinbelow, which corresponds to signal S_U). This is because Plausibility[U] for the UR is always 1.0, which would unacceptably force the estimated probability to be at least 0.5 regardless of whether any conflict has been encountered. (Although this creates potential problems when values are normalized, since different types of values are being normalized, the ability of the diagnostic tester to determine the sufficiency of testing does not appear to be adversely affected.) The conclusion with the highest probability is automatically considered a hypothesis (signal S_{CP1}). A determination is then made whether any other conclusions have probabilities close enough to the maximum to be considered a hypothesis as well. A threshold function is used to make this determination:

If $S_{P1} \leq 0.1$, then Threshold = $0.5 * S_{P1}$
If $S_{P1} \geq 0.5$, then Threshold = $0.9 * S_{P1}$
Else Threshold = $S_{P1} * (0.4 + S_{P1})$.

If any conclusion has a probability value that exceeds th threshold, then that conclusion is also considered a hypoth sis (signal S_{CPn}).

In accordance with the present invention, the Dempster-Shafer method is modifi d so that direct conflict betw en test outcomes and hypotheses results in an ov rall increase in uncertainty in th system. This modification entails the introduction of a new diagnostic conclusion, r ferred to herein as the "unanticipated result" (UR). The UR is never denied, and it is supported only in the event of a conflict. The current support value for the UR, i.e., signal S_U, is computed as follows in the absence of conflict:

$$S_U = S_U * (\text{Tests} - 1)/\text{Tests}.$$

In the event of a conflict, a S_U value is calculated as above, and an additional computation is made using this value to derive the S_U signal value used to determine the sufficiency of the testing:

$$S_U = S_U + (\text{Conflicts} * K * \text{Confidence}[t_k])/\text{Tests}$$

where

Conflicts =	the number of times a conflict is encountered
Tests =	the number of tests performed and actually evaluated so far (does not include tests for which outcomes have been inferred; each repetition of the same test is counted)

The new current total support for each conclusion in the model, $\text{Support}_{\text{Total}}[c_i]$, based on the accumulated test data currently inputted, is then computed:

$$\text{Support}_{\text{Total}}[c_i] = (\text{Support}_{\text{Total}}[c_i] * \text{Support}[c_i] + \text{Uncertainty} * \text{Support}[c_i] + \text{Support}_{\text{Total}}[c_i] * (1-\text{Confidence}[t_k]))/(1-K).$$

If $\text{Support}[c_i]$ is less than 1/Conclusions, where the Conclusions value is the number of conclusions in the diagnostic model, then $\text{Support}[c_i]$ is reduced by 25% to gradually remove the conclusion from consideration. Next, a new uncertainty value is computed:

$$\text{Uncertainty} = (\text{Uncertainty} * (1-\text{Confidence}[t_k]))/(1-K).$$

Finally, the support values $\text{Support}[c_i]$ are normalized as indicated above. Each total support value is normalized to sum to 1.0 minus the support for the UR:

$$\text{Support}_{\text{Total}}[c_i] = \text{Support}_{\text{Total}}[c_i] * (1-S_U)/\Sigma_j \text{Support}_{\text{Total}}[c_j]$$

In addition to computing the support values for the conclusions in the model, the denial values must also be computed. Denial is computed as follows:

$$\text{Denial}_{\text{Total}}[c_i] = \text{Denial}_{\text{Total}}[c_i] + \text{Denial}[c_i].$$

From the denial computation, plausibility is computed:

$$\text{Plausibility}[c_i] = 1 - (\text{Denial}_{\text{Total}}[c_i]/\text{Tests}).$$

To summarize the computational flow, as shown in Fig. 11, the first step (SS600) is to initialize the values for total

support and denial of conclusions, plausibility and uncertainty, support of the UR; and to define the initial current hypotheses. (All of the possible model conclusions advantageously are selected as the initial hypotheses.) The next step (SS602) is to perform a t st select d as described hereinabove, and valuate the outcome. Th n, (SS604), a confidence value is assigned to the test outcome; and the support and denial for ach conclusion are calculated based on the test outcome confidence value (step SS606). The next step (SS608) determines if the test outcome conflicts with all current hypotheses. Then the measure of internal conflict K is obtained (SS610) based on the old total support values and the pr sent test outcome support values for all of the conclusions. The present value of the UR support is then computed based on the number of tests evaluated, if the present test outcome is not a conflict; and based on the number of tests evaluated and the number of conflicts, if the present test outcome is a conflict (SS612). Next (SS614), the new total support value for each conclusion is computed based on the old total support value, the present test outcome support value and confidence value, the old uncertainty, and K. Then a new uncertainty value is computed based on the old uncertainty value, the present test outcome confidence value and K (SS616). The next step (SS618) is to normalize the total support value for each conclusion based on the old total support value, and the present UR support value. Then (SS620), a new total denial is computed for each conclusion based on the old total denial and the present test outcome denial value. Next (SS622), the present plausibility is computed for each conclusion based on the present total denial and the number of tests evaluated. The current hypothesis/hypotheses (signals S_{CP}) is/are selected (SS624) based on the present total support and the plausibility for each conclusion. Finally (SS626), the sufficiency of testing is evaluated based on values derived for the two highest levels of certainty, S_{P1} and S_{P2}, and the value of the UR support, S_U, in the manner to be described in more detail next, to determine whether to continue or terminate further testing, and whether to declare a diagnosis.

TERMINATING THE DIAGNOSTIC PROCESS

The testing sufficiency evaluation approach of the present invention operates to recognize when sufficient differentiation between levels of certainty regarding the validity of alternative candidate diagnoses exists. In the preferred implementation described herein, a neural network is trained to recognize patterns in the levels of certainty indicative of whether a diagnosis can be made or there is so much conflict that the diagnosis process should be halted. Further, the preferred neural network is configured to be generic, that is, it can be used without modification or retraining for different diagnosis (classification) problems and different diagnosis models.

Referring to Fig. 12, a neural network 100 according to the present invention preferably comprises a set 110 of at least first, second, third and fourth input nodes 111, 112, 113 and 114, respectively. Each of the input nodes has first, s cond and third outputs weighted by a predetermined fixed weight. Input nodes 111 and 112 respectively receive certainty signals S_{P1} and S_{P2} as an input. Input node 113 preferably receives uncertainty signal S_U, but this input need not be present; and input node 114 is a bias node receiving a predetermined, e.g., unity, bias signal.

If desired, additional input nodes can be provided which receive additional certainty signals corresponding to the successive next highest levels of certainty associated with the model conclusions. Such additional certainty signals can also include signal S_N referred to hereinabove corresponding to the level of certainty that some conclusion other than the model conclusions and the UR is the correct diagnosis. However, for the disclosed preferred embodiment, additional input nodes are not necessary. Since the testing sufficiency determination does not depend on the character of the conclusions constituting the leading hypothesis, only one node is needed corresponding to the highest level of certainty (estimated probability value in the preferred embodiment). In addition, since only a single failure is being isolated by any given analysis, it is only necessary to compare the highest probability value with the next highest in order to determine whether the highest is "high enough."

Neural network 100 further comprises at least one set 120 of first, second, third and fourth intermediate nodes 121, 122, 123 and 124 each having an output weighted by a predetermined fixed weight. Intermediate node 111 receives the sum of the first weighted outputs of input nodes 110 as an input, intermediate node 122 receives the sum of the second weighted outputs of input nodes 110 as an input, intermediate node 123 receives the sum of the third weighted outputs of input nodes 110 as an input, and intermediate node 124 is a bias node like node 114 receiving the predetermined bias signal. At least one intermediate layer is preferred, but not necessary. Fig. 13 shows a viable two layer neural network which has been implemented.

The always active bias nodes provided in the input and intermediate layers are generally required to ensure that there is always some activity coming into each node of the upper layers, and to prevent singularities.

Neural network 100 also comprises a single output node 130, responsive to the sum of said weighted outputs of intermediate nodes 120, for producing output signal S_S indicativ of whether sufficient test data has been evaluated to declare a diagnosis. Only a single output node is needed for the prelerred embodiment becaus only of simple "y s/ no" determination needs to b mad .

The output weights of input and intermediate nodes 110 and 120 correspond to a model of expert data correlating combinations of at least certainty signal values, and preferably certainty and uncertainty signal values, with at least

one xpert opinion regarding the ability to d clare a diagnosis on the basis of each combination of such signal values. The expert data model can either be specific to a type of system being diagnosed, or as will be described in more detail h r inafter, can be gen ric to syst ms in g neral.

The node output weights advantageously are obtained by training a backpropagation neural network having the same architecture as said neural network using empirical c rtainty and uncertainty signal training data obtained from testing of real systems, and conclusions derived from at least one xpert regarding the sufficiency of the information represented by the combinations to declare a diagnosis for a specific system to be tested.

Alternatively, and preferably, the backpropagation neural network is trained using normalized randomly generated certainty and uncertainty signal training data, and conclusions derived from at least one expert regarding the sufficiency of the information represented by said combinations to declare a diagnosis for systems in general.

Preferably, the estimated probability values of the certainty and uncertainty signals are applied as the inputs to nodes 111 and 112. The training data includes first, second and third unambiguous combinations in which the data sufficiency determination is obvious. Advantageously, one unambiguous combination comprises certainty signal S_{P1} having a probability value corresponding to 100% and certainty signal S_{P2} and uncertainty signal S_U having zero values. Another unambiguous combination advantageously comprises certainty signal S_{P1} and uncertainty signal S_U each having a probability value corresponding to 100%, and certainty signal S_{P2} having a zero probability value. The third unambiguous combination advantageously comprises both of the certainty signal S_{P1}, S_{P2} probability values having uniform probabilities and the uncertainty signal S_U probability value having a zero value.

The neural network training data preferably also includes two data sets each having a predetermined number of ambiguous combinations wherein:

both data sets have certainty signal probability values within a closed interval [0,1] generated at random according to a lognormal distribution;
a first one of the data sets has uncertainty signal probability values generated at random according to a lognormal distribution;
a second one of the data sets has uncertainty signal probability values set to zero;
the values so generated are adjusted by normalizing the certainty signal probability values in each ambiguous combination to sum to 1 - S_U;
all normalized certainty signal probability values and the uncertainty signal probability values less than or equal to a predetermined value based on the number of elements in the system are set to zero;
the resultant certainty and uncertainty signal values in each of the ambiguous combinations are normalized to sum to the value one; and
the larger of the resultant normalized certainty signal probability values is designated as the value input to node 111 in each of the ambiguous combinations where the certainty signal probability values are unequal.

Preferably, the sum of the weighted outputs inputted to each of the intermediate nodes 120 and to output node 130 is processed in the respective node with a sigmoidal activation function, which preferably is also logistic, and preferably the function $1/(1+e^{-x})$, where x is the unweighted output of a given node.

An exemplary set of training data and the survey data from which the training data was derived are shown in the following charts:

NEURAL NETWORK TRAINING DATA				
Case	Node 1	Node 2	Node 3	Answer
1	1.00	0.00	0.00	1.00
2	0.50	0.00	0.50	1.00
3	0.50	0.50	0.00	0.00
4	0.47	0.30	0.23	1.00
5	0.59	0.41	0.00	0.00
6	0.50	0.50	0.00	0.00
7	0.39	0.34	0.27	1.00
8	0.64	0.36	0.00	1.00
9	0.58	0.42	0.00	0.00
10	0.52	0.48	0.00	0.00
11	0.32	0.22	0.46	1.00
12	0.76	0.24	0.00	1.00

(continued)

NEURAL NETWORK TRAINING DATA				
Case	Node 1	Node 2	Node 3	Answer
13	0.51	0.49	0.00	0.00
14	0.51	0.49	0.00	0.00
15	0.56	0.44	0.00	0.00
16	0.67	0.33	0.00	1.00
17	0.66	0.34	0.00	1.00
18	0.58	0.42	0.00	0.00
19	0.72	0.28	0.00	1.00
20	0.55	0.45	0.00	0.00
21	0.70	0.30	0.00	1.00
22	0.52	0.48	0.00	0.00
23	0.67	0.33	0.00	1.00
24	0.27	0.25	0.48	1.00
25	0.50	0.50	0.00	0.00
26	0.52	0.48	0.00	0.00
27	0.62	0.38	0.00	1.00
28	0.14	0.11	0.76	1.00
29	0.43	0.27	0.30	1.00
30	0.68	0.32	0.00	1.00
31	0.50	0.25	0.25	1.00
32	0.53	0.47	0.00	0.00
33	0.51	0.49	0.00	0.00
34	0.54	0.46	0.00	0.00
35	0.63	0.37	0.00	1.00
36	0.38	0.32	0.30	1.00

SURVEY

ANSWER	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	UR
	.47					.30					.23
				.22	.36	.16				.25	
				.40	.19			.40			
				.39						.34	.27
	.17				.41	.23	.19				
			.19	.17		.27				.37	
			.32	.21				.18		.29	
				.11	.11	.14			.21	.14	.30
	.64	.16		.20							
	.29		.36				.16			.20	
				.17	.21	.22	.19		.20		
			.23	.24	.20			.19		.15	
	.44		.26							.30	
	.33					.22	.26	.19			
		.21	.18	.18		.42					
	.20			.26			.16			.19	.19
					.16	.35	.18	.14		.17	
	.23		.25						.17	.34	
	.22			.21	.18			.24			.16
	.11			.13				.21	.12	.25	.17
	.15					.50	.19			.16	
		.39					.24			.18	.19
			.17	.20		.20		.24	.19		
				.23			.54		.22		
	.13		.13	.18	.20			.22	.14		
					.16	.35	.18	.14		.17	
	.52			.26			.22				
	.17				.41	.23	.19				

ANSWER	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	UR
				.16	.21				.23		.40
	.17		.22			.11	.15	.20			.14
	.15		.25	.25			.18		.16		
	.52		.48								
		.21				.39	.24			.16	
		.10		.08	.06	.07	.06		.07		.56
	.15					.50	.19			.16	
	.16		.18		.16		.29				.20
		.25			.21		.53				
				.25				.50			.25
				.39						.24	.27
						.25	.40	.35			
	.17	.19				.25	.16	.24			
	.16				.45				.39		
	.16			.41	.24				.21	.14	
						.19	.31		.26		.24

Also shown in the training data are the answers selected according to the answers provided by the polled experts regarding the ability to make a confident diagnoses based on the probability value combinations. Since it was desired that neural network 100 be conservative in making a termination determination, if any expert indicated that a combination warranted termination, that answer was selected as the answer to be used in training the network. It will be appreciated that the survey included combinations containing ten probability values plus a UR probability value. The probability values were generated as indicated above, with all values less than or equal to 0.1 being set to 0.0. The surveyed experts were engineers who were familiar with and had used STAMP. The experts were instructed to assess the survey combinations on the basis of the following assumptions:

1. A system that has failed is being tested based on a diagnostic model.
2. The c_n numbers represent probabilities derived from the testing that a unit(c_n) within the system is the failure.
3. The failure events are independent and a testability analysis has shown that each of the conclusions listed is reachable and unique in a perfect information environment.
4. The UR value represents the probability that something has occurred in the system that the model currently cannot account for.

The training data set forth hereinabove has been applied to a backpropagation neural network having random initial output weight values and trained using a conventional backpropagation training program wherein each combination of certainty and uncertainty signal values was repeatedly applied to the corresponding input nodes of the neural network. An error value was computed following each application corresponding to how much the actual output of node 130 differed from the expected output for the combination as defined by the selected expert answer in the training data. Specifically, the error was computed as the squared error:

$$E = 1/2 \sum_{p=0}^{n_p-1} \sum_{i=0}^{n_o-1} (T_i^{(p)} - O_i^{(p)})^2$$

wher

E =	the measure of squared error
n_p =	the number of patterns in the training set
n_o =	the number of output nodes
p =	the current input pattern
i =	the current output/target node
$T_i^{(p)}$ =	the expected output of node i given pattern p
$O_i^{(p)}$ =	the actual output of node i given pattern p

From the value E, a correction term is computed which is then propagated backward through the network, adjusting the node weights as it goes. The correction term is computed from the partial derivative of the error with respect to the weights. The weight adjustment occurs as follows:

$$w_{ji}^{(k)}(t+1) = \eta \sum_{p=0}^{n_p-1} \delta_i^{(p,k} O_j^{(p,k-1)} + w_{ji}^{(k)}(t) + \alpha \Delta w_{ji}^{(k)(t)}$$

where

$w_{ji}^{(k)}(t)$ =	the weight from node j to node i at time t for layer k
η =	the learning rate
$O_j^{(p,k-1)}$ =	the output of node j for combination p at layer k-1
k =	the current layer
p =	the current pattern
n_p =	the number of patterns
$\delta_i^{(p,k)}$ =	the correction term for node i at layer k resulting from pattern p
α =	momentum coefficient
$\Delta w_{ji}^{(k)}(t)$ =	change in the weight at time t.

The correction term, $\delta_i^{(p,k)}$, is computed as follows:
Case 1: (the output layer)

$$\delta_i^{(p,k)} = (T_i^{(p)} - O_i^{(p,k)}) O_i^{(p,k)} (1 - O_i^{(p,k)})$$

Case 2: (all hidden layers)

$$\delta_i^{(p,k)} = \left(\sum_{j=0}^{n_{k-1}+1} \delta_i^{(p,k-1)} w_{ji}^{(k-1)}\right) O_i^{(p,k)} \left(1 - O_i^{(p,k)}\right)$$

Although the use of a backpropagation neural network is preferred, other types of neural networks can be used. For example, counterpropagation as developed by Robert Hecht-Nielson provides essentially the same functionality with a different architecture. Hopfield networks, Adaline networks, and other supervised learning networks could also be used.

As the training data is repeatedly presented to the neural network, the network weights are modified gradually, following the error surface defin d by the network weight space down the gradient to a local minimum. When th n twork settles, it contains a solution to the mapping problem.

The node output weights which resulted from this training are:

the weights of the first, second and third outputs of input node 111 are (-9.640), 5.049, and (-1.624), resp ctively;
the weights of the first, second and third outputs of input nod 112 are 15.641, (-8.491), and 2.436, respectively;
the weights of the first, second and third outputs of input node 113 are (-6.680), 3.627, and (-1.237), resp ctiv ly;
the weights of the first, second and third outputs of input node 114 are (-0.422), 0.442, and (-0.427), respectiv ly; and
the weights of the outputs of int rmediate nodes 121, 122, 123 and 124 are, r spectively, (-19.214), 11.457, (-2.483) and 4.081.

This collection of weights has proven to make testing sufficiency determinations which correlate highly with the opinions of experts exposed to the same data. Specifically, neural network 100 has been tested with a set of 2601 randomly generated test data representing all permutations of three numbers to two decimal places under the following constraints:

1. The numbers were all in the closed interval [0,1].
2. The numbers all summed to 1.0.
3. The first number was always greater than or equal to the second number.

Twenty of these cases were randomly selected as a test survey and submitted to the same group of five experts used to generate the training data. On average, 4.25 of the experts agreed with neural network 100 on each test case. In one case, neural network 100 indicated termination was not appropriate, while four of the experts said it was appropriate. This case was at the decision boundary of the neural network, and could have been decided either way. Thus, overall, the performance of neural network 100 was in agreement with the experts.

It will be appreciated by those skilled in the art that the invention has been described with respect to exemplary embodiments, and that numerous modifications can be made therein without departing from the scope of the invention.

Claims

1. Automatic test data evaluation apparatus for use in a diagnostic tester that declares a diagnosis on the basis of localisation or isolation of failed system elements of a system having a defined number of functional elements, said apparatus comprising:

   means for selecting the next test to be performed on the system to be tested;
   means for generating the corresponding test data and supplying them to the system to be tested;
   means for sensing and collecting predetermined system operating parameters;
   evaluating means (54), responsive to at least one inputted test signal corresponding to test data S_T relating to at least one predetermined parameter of the system, for producing using a probabilistic evidential reasoning method:

      first (S_{CP1}) and second (S_{CP2}) candidate signals corresponding respectively to first and second possible diagnoses of the condition of the system respectively having the first and second highest levels of certainty of being valid, and
      first (S_{P1}) and second (S_{P2}) certainty signals corresponding respectively to values of said first and second highest levels of certainty; and

   characterized by testing sufficiency means (56), responsive to said first and second certainty signals, for producing an output signal (S_S) indicative of whether sufficient test data has been evaluated to declare a diagnosis, said testing sufficiency means comprising a neural network having an output node (130') and at least three input nodes (111',112',114') respectively receiving said first and second certainty signals and a predetermined bias signal as an input, said input nodes having weighted outputs, the output weights corresponding to a model of expert data correlating combinations of certainty signals with at least one expert opinion regarding the ability to declare a diagnosis on the basis of each combination of certainty signal values.

2. The apparatus of claim 1 wherein:

   said evaluating means also produces an uncertainty signal S_u corresponding to a m asur of the unc rtainty that the evaluated at least one test signal can be validly evaluated; and
   said neural n twork comprises:

a set (110) of first (111), s cond (112), third (113) and fourth (114) input nod s each having first, second and third outputs weighted by a predetermined fixed weight, said first (111) and second (112) input nodes respectively receiving said first (S_{P1}) and s cond (S_{P2}) certainty signals as an input, said third input nod (113) receiving said uncertainty signal (S_u), and said fourth input node (114) rec iving said predetermined bias signal (BIAS);
a set (120) of first (121), second (122), third (123) and fourth (124) intermediate nodes each having an output weighted by a predetermined fixed weight, and said first intermediate node (121) receiving the sum of the first weighted outputs of said input nodes as an input, said second intermediate node (122) receiving the same of the second weighted outputs of said input nodes as an input, said third intermediate node (123) receiving the sum of the third weighted outputs of said input nodes as an input, and said fourth intermediate node (124) receiving said predetermined bias signal (BIAS); and
an output node (130), responsive to the sum of said weighted outputs of said intermediate nodes, for producing said output signal (S_s), the output weights of said input and intermediate nodes corresponding to a model of expert data correlating combinations of certainty and uncertainty signal values with at least one expert opinion regarding the ability to declare a diagnosis on the basis of each combination of certainty and uncertainty signal values, said testing sufficiency means thereby also evaluating said uncertainty signal to produce said output signal.

3. The apparatus of claim 2 wherein:

said evaluating means also produces a signal S_N corresponding to a measure of the level of certainty that a diagnosis not corresponding to said first or second candidate signals or to said uncertainty signal is a valid diagnosis; and
said testing sufficiency means also evaluates said signal S_N to produce said output signal.

4. The apparatus of claim 2, wherein said evaluating means (54) comprises:

means for storing a model of predetermined information flow relationships within the system under test;
means for associating said test signals with sets of possible causes in accordance with said model, and for ascertaining the intersections of said sets of possible causes for combinations of test signals, said candidate signals being derived from said intersections; and
means for determining for each candidate signal a measure of the level of certainty that it represents a valid diagnosis.

5. The apparatus of claim 4, wherein said evaluating means (54) comprises means for determining the degree to which a conflict exists between at least said first candidate signal and said at least one test signal indicative of the level of certainty that an unanticipated result (UR) has been obtained, said uncertainty signal having a value corresponding to said UR level of certainty.

6. The apparatus of claim 1 wherein the values of said first and second highest levels of certainty are probability values.

7. The apparatus of claim 2, wherein said uncertainty measure has a probability value.

8. The apparatus of claim 5, wherein said UR determining means comprises:

means for defining a plurality of conclusions corresponding to possible diagnoses of the system;
means for assigning a confidence value to each successively inputted test signal;
means for calculating the support and denial for each conclusion based on said confidence value of the currently inputted test signal;
means for determining if the currently inputted test signal conflicts with a then selected set of said conclusions corresponding to candidate signals;
means for obtaining a measure of internal conflict based on accumulated total support values and the current test signal support values for all of said conclusions;
means for computing the present value of said uncertainty signal based on the number of test signals valuated, if the present test signal is not a conflict; and based on the number of test signals valuat d and the number of conflicts, if the present test signal is a conflict;
means for computing a new total support value for ach conclusion based on the old total support value, the

present test signal support value and confidence value, an old uncertainty value, and said measure of int rnal conflict;

means for computing a new uncertainty value bas d on the old uncertainty value, the present t st signal confid nce value and said measure of internal conflict;

means for normalizing the total support value for each conclusion based on the old total support value, and the present uncertainty signal value;

means for computing a new total denial for each conclusion based on an old total denial and the present test signal denial value;

means for computing the present plausibility for each conclusion based on the present total denial and the number of test signals evaluated;

means for selecting the current set of candidate signals based on the present total support and the plausibility for each conclusion.

9. Apparatus according to claim 2, wherein said output weights of said input (111-114) and intermediate (121-124) nodes have values obtained by training a backpropagation neural network having the same architecture as said neural network using empirical certainty and uncertainty signal training data obtained from testing of real systems, and conclusions derived from at least one expert regarding the sufficiency of the information represented by said combinations to declare a diagnosis for a specific system to be tested.

10. The apparatus of claim 9, wherein said output weights of said input (111-114) and intermediate (121-124) nodes have generic values obtained by training a backpropagation neural network having the same architecture as said neural network using normalized randomly generated certainty and uncertainty signal training data, and conclusions derived from at least one expert regarding the sufficiency of the information represented by said combinations to declare a diagnosis for systems in general.

11. The apparatus of claim 5, wherein the values of said certainty and uncertainty signals correspond to probability values.

12. The apparatus of claim 11, wherein said training data includes first, second and third unambiguous combinations in which the data sufficiency determination is obvious, said first unambiguous combination comprising said first certainty signal having a value corresponding to 100% probability and said second certainty signal and said uncertainty signal having zero values, said second unambiguous combination comprising said first certainty signal and said uncertainty signal each having a value corresponding to 100% probability and said second certainty signal having a zero value, and said third unambiguous combination comprising both of said certainty signals having values corresponding to uniform probabilities and said uncertainty signal having a zero value.

13. The apparatus of claim 12, wherein said training data includes two data sets each having a predetermined number of ambiguous combinations wherein:

both data sets have certainty signal values within a closed interval [0,1] generated at random according to a lognormal distribution;

a first one of said data sets has uncertainty signal values generated at random according to a lognormal distribution;

a second one of said data sets has uncertainty signal values set to zero;

the values so generated are adjusted by normalizing the certainty signal values in each ambiguous combination to sum to $(1 - S_U)$, all normalized certainty signal values and the uncertainty signal values less than or equal to a predetermined value based on the number of elements in the system are set to zero; and then the resultant certainty and uncertainty signal values in each of said ambiguous combinations are normalized to sum to the value one; and

the larger of the resultant normalized certainty signal values is designated as the first certainty signal value in each of said ambiguous combinations where the certainty signal values are unequal.

14. The apparatus of claim 11, wherein:

the sum of the weighted outputs inputted to each of the intermediate nodes and the output mode is processed in the r spective node with a sigmoidal activation function;

the weights of the first, second and third outputs of the first input node are (-9.640), 5.049, and (-1.624), resp ctively;

the w ights of the first, second and third outputs of the second input node are 15.641, (-8.491), and 2.436, respectively;
the weights of the first, second and third outputs of the third input node ar (-6.680), 3.627, and (-1.237), resp ctively;
the weights of the first, second and third outputs of the fourth input node are (-0.422), 0.442, and (-0.427), respectively;
the weight of the output of the first intermediate node is (-19.214);
the weight of the output of the second intermediate node is 11.457;
the weight of the output of the third intermediate node is (-2.483); and
the weight of the output of the fourth intermediate node is 4.081.

15. The apparatus of claim 14, wherein said activation function is logistic.

16. The apparatus of claim 15, wherein said activation function is $1/(1+e^{-x})$, where x is the unweighted output of a given node.

17. A diagnostic tester for declaring a diagnosis on the basis of localisation and isolation of failed system elements of a system having a defined number of functional elements the tester comprising the apparatus according to any of the preceding claims, the tester further comprising input means (13,26,34,42,52) for supplying test signals to said evaluating means.

18. The diagnostic tester of claim 17, wherein said input means comprises operator actuated input means (13,26) for entering test data relating to at least one predetermined aspect of the system, and for generating test signals corresponding to the test data.

19. The diagnostic tester of claim 17, wherein said input means comprises automatic test means (34) responsive to a control signal for performing selected tests on the system, and for generating test signals corresponding to the test results.

20. The diagnostic tester of claim 19, further comprising:
control means (32) responsive to said output signal for producing said control signal to cause said automatic testing means to perform at least one further selected test on the system if said output signal indicates that insufficient test data has been evaluated; and for producing a conclusion signal indicative of a diagnosis in accordance with said first candidate signal if said output signal indicates that sufficient test data has been evaluated.

21. The diagnostic tester of claim 20, wherein said control means (32) produces said control signal to select said at least one further selected test in accordance with at least one prior evaluation of test signals.

22. The diagnostic tester of claim 17 further comprising:

a display (12,22,36); and
means (24) responsive to said output signal for controlling said display to indicate the need for additional test data and for controlling said input means to accept a further at least one test signal for evaluation by said evaluating means if said output signal indicates that insufficient test data has been evaluated; and for controlling said display responsive to said first candidate signal to indicate a diagnosis if said output signal indicates that sufficient test data has been evaluated.

23. A diagnostic tester according to any of claims 17 to 22 and/or comprising apparatus according to any of claims 1 to 16 the tester comprising an arrangement for testing a system according to a set of defined relationships between a plurality of sources for providing information about the system and a plurality of conclusions about the nature or condition of the system, said tester comprising:

first means (34) for successively selecting (551) an information source from among the plurality of information sources for interrogation according to the relative amount of information provided by each information source until all of the information sources have been selected or the information which would b provid d th reby has b en determin d;
second means (34) for successively further selecting an information source from among the plurality of information sources for interrogation according to which information source will increase the l vel of certainty that

a selected candidate conclusion constitutes a valid diagnosis of the system being tested.

24. The diagnostic tester of claim 23 wherein said second selecting means comprises:

means for assigning a confidence value to the information provided by an information source;
m ans responsive to said confidence values and to th information provided by interrogated information sources for computing a level of certainty for each of the conclusions that it constitutes a valid diagnosis;
means for selecting candidate conclusions according to the relative values of the computed levels of certainty for each conclusion.

25. The diagnostic tester of claim 24 further comprising:
first means for identifying, if more than one candidate conclusion has been selected, which information sources, if any, depend on one of the two candidate conclusions with the then highest levels of certainty and not the other, and, if more than one such information source is identified, identifying which of such information sources furnishes the most information about the support for the candidate conclusion on which it depends.

26. The diagnostic tester of claim 25 further comprising:
second means, responsive to said first identifying means determining that no information source satisfies the identification criteria of said first identifying means, and responsive to said selecting means having then selected only one candidate conclusion, for identifying the information source, if any, that provides the most support for the candidate conclusion having the then highest level of certainty, if more than one candidate conclusion has then been selected, or for the candidate conclusion, if only one candidate conclusion has then been selected.

27. The diagnostic tester of claim 26 further comprising:
third means, responsive to said second identifying means determining that no information source satisfies the identification criteria of said second identifying means, for identifying the information source, if any, that supports the most conclusions other than the candidate conclusion having the then highest level of certainty.

Pat ntansprüche

1. Automatische Testdatenauswertevorrichtung zur Verwendung in einem diagnostischen Tester, der auf Basis der Lokalisation oder Isolation von versagten Systemelementen eines Systems mit einer definierten Anzahl funktionaler Elemente eine Diagnose abgibt, mit:

einem Mittel zum Auswählen des nächsten durchzuführenden Tests auf dem zu testenden System,

einem Mittel zum Generieren der korrespondierenden Testdaten und zum Liefern derselben an das zu testende System,

einem Mittel zum Wahrnehmen und Sammeln vorbestimmter Systembetriebsparameter,

einem Auswertungsmittel (54), das sensibel ist für mindestens ein eingegangenes Testsignal, das mit Testdaten S_T korrespondiert, welches sich auf mindestens einen vorbestimmten Parameter des Systems bezieht, zum Produzieren unter Verwendung einer probabilistischen nachweisenden Begründungsmethode (?), von

ersten (S_{CP1}) und zweiten (S_{CP2}) Kandidatensignalen, die jeweils mit ersten und zweiten möglichen Diagnosen des Zustands des Systems korrespondieren und jeweils den höchsten bzw. zweithöchsten Bestimmtheitsgrad, gültig zu sein, haben und

ersten (S_{P1}) und zweiten (S_{P2}) Bestimmtheitssignalen, die jeweils mit den Werten des höchsten bzw. zweithöchsten Bestimmtheitsgrads korrespondieren, und

gekennzeichnet durch Mittel zum Testen der Hinlänglichkeit (56), sensibel für die ersten und zweiten Bestimmtheitssignale, zum Produzieren eines Ausgangssignals (S_S), das anzeigt, ob hinlänglich viele Testdaten ausg wertet worden sind, um eine Diagnose abzugeben, wobei das Mittel zum Testen der Hinlänglichkeit ein n uronales Netzwerk aufweist, mit einem Ausgangsknoten (130') und mindestens drei Eingangsknoten (111', 112', 114'), die jeweils die ersten und zweiten Bestimmtheitssignale und ein vorher festgesetztes Biassignal als Eingang empfan-

gen, wobei die Eingangsknoten gewichtete Ausgänge haben, die mit einem Modell aus Exp rtendaten korr spondieren, wobei die Expertendaten Kombinationen von Bestimmtheitssignalen mit mindestens einer Expertenmeinung in b zug auf die Fähigkeit, eine Diagnose auf Basis jeder Kombination von Bestimmtheitssignalwerten abzugegen, korrelieren.

2. Die Vorrichtung nach Anspruch 1, wobei

das Auswertungsmittel auch ein Unbestimmtheitssignal (S_u) produziert, das mit einem Maß der Unbestimmtheit korrespondiert, daß das ausgewertete mindestens eine Testsignal gültig ausgewertet werden kann, und

das neuronale Netzwerk folgendes aufweist:

einen Satz (110) erster (111), zweiter (112), dritter (113) und vierter (114) Eingangsknoten, von denen jeder erste, zweite und dritte Ausgänge hat, die durch ein vorher festgesetztes, bestimmtes Gewicht gewichtet sind, wobei die ersten (111) und zweiten (112) Eingangsknoten jeweils die ersten (S_{P1}) und zweiten (S_{P2}) Bestimmtheitssignale als Eingang empfangen, der dritte Eingangsknoten (113) das Unbestimmtheitssignal (S_u) empfängt und der vierte Eingangsknoten (114) das vorher festgesetztes Biassignal (BIAS) empfängt,

einen Satz (120) erster (121), zweiter (122), dritter (123) und vierter (124) mittlerer Knoten, von denen jeder einen durch ein vorher festgesetztes bestimmtes Gewicht gewichteten Ausgang hat, wobei der erste mittlere Knoten (121) die Summe der ersten gewichteten Ausgänge der Eingangsknoten als Eingang empfängt, der zweite mittlere Knoten (122) dieselben der zweiten gewichteten Ausgänge der Eingangsknoten als Eingang empfängt, der dritte mittlere Knoten (123) die Summe der dritten gewichteten Ausgänge der Eingangsknoten als Eingang empfängt und der vierte mittlere Knoten (124) das vorher festgesetzte Biassignal (BIAS) empfängt, und

einen Ausgangsknoten (130), der sensibel ist für die Summe der gewichteten Ausgänge der mittleren Knoten, zum Produzieren des Ausgangssignals (S_S), wobei die Ausgangsgewichte der Eingangs- und mittleren Knoten mit einem Modell von Expertendaten korrespondieren, wobei die Expertendaten Kombinationen von Bestimmtheits- und Unbestimmtheitssignalwerten mit mindestens einer Expertenmeinung bezüglich der Fähigkeit korrelieren, eine Diagnose auf Basis jeder Kombination von Bestimmtheits- und Unbestimmtheitssignalwerten abzugeben, wodurch das Mittel zum Testen der Hinlänglichkeit das Unbestimmtheitssignal ebenfalls auswertet, um das Ausgangssignal zu produzieren.

3. Die Vorrichtung nach Anspruch 2, wobei

das Auswertungsmittel auch ein Signal (S_N) produziert, das mit einem Maß des Bestimmtheitsgrads korrespondiert, daß eine nicht mit den ersten oder zweiten Kandidatensignalen oder mit dem Unbestimmtheitssignal korrespondierende Diagnose eine gültige Diagnose ist, und

das Mittel zum Testen der Hinlänglichkeit auch das Signal (S_N) auswertet, um das Ausgangssignal zu produzieren.

4. Die Vorrichtung nach Anspruch 2, wobei das Auswertungsmittel (54) folgendes aufweist:

ein Mittel zum Speichern eines Modells von Flußbeziehungen vorher festgelegter Information innerhalb des im Test befindlichen Systems,

ein Mittel zum Assoziieren des Testsignals mit Sätzen möglicher Ursachen in Übereinstimmung mit dem Modell und zum Ermitteln der Schnittpunkte der Sätze möglicher Ursachen für Kombinationen von Testsignalen, wobei die Kandidatensignale von den Schnittpunkten hergeleitet werden, und

ein Mittel zum Bestimm n eines Maßes des Bestimmtheitsgrads für jedes Kandidatensignal, daß es eine gültige Diagnos repräsentiert.

5. Die Vorrichtung nach Anspruch 4, wobei das Auswertungsmittel (54) Mittel aufweist zum Bestimmen des Grads, zu dem in Konflikt zwischen mindestens dem ersten Kandidatensignal und mindest ns einem T stsignal existiert,

das den Bestimmtheitsgrad anzeigt, daß ein nicht antizipiertes Ergebnis (UR) erhalt n worden ist, wobei das Unbestimmtheitssignal einen mit dem UR-Bestimmtheitsgrad korrespondierenden Wert hat.

6. Die Vorrichtung nach Anspruch 1, wobei die Werte der höchsten und zw ithöchsten Bestimmtheitsgrade Wahrscheinlichkeitswerte sind.

7. Die Vorrichtung nach Anspruch 2, wobei das Unbestimmtheitsmaß einen Wahrscheinlichkeitswert hat.

8. Die Vorrichtung nach Anspruch 5, wobei das UR-Bestimmungsmittel folgendes aufweist:

   ein Mittel zum Definieren einer Vielzahl von Schlußfolgerungen, die mit möglichen Diagnosen des Systems korrespondieren,

   ein Mittel zum Zuweisen eines Vertrauenswerts zu jedem fortfolgend eingegangenen Testsignal,

   ein Mittel zum Berechnen der Zustimmung und Ablehnung für jede Schlußfolgerung basierend auf dem Vertrauenswert des gegenwärtig eingegangenen Testsignals,

   ein Mittel zum Bestimmen, ob das gegenwärtig eingegangene Testsignal einem dann ausgewählten Satz der mit Kandidatensignalen korrespondierenden Schlußfolgerungen widerspricht,

   ein Mittel zum Bestimmen eines Maßes internen Widerspruchs basiert auf akkumulierten totalen Zustimmungswerten und den gegenwärtigen Testsignalstützwerten für alle Schlußfolgerungen,

   ein Mittel zum Berechnen des gegenwärtigen Werts des Unbestimmtheitssignals basiert auf einer Anzahl ausgewerteter Testsignale, wenn das gegenwärtige Testsignal nicht einen Widerspruch bildet, sowie basiert auf der Anzahl ausgewerteter Testsignale und der Anzahl Widersprüche, wenn das gegenwärtige Testsignal einen Widerspruch bildet,

   ein Mittel zum Berechnen eines neuen totalen Zustimmungswerts für jede Schlußfolgerung basiert auf dem alten totalen Zustimmungswert, dem gegenwärtigen Testsignalstützwert und Vertrauenswert, einem alten Unbestimmtheitswert und dem Maß internen Widerspruchs,

   ein Mittel zum Berechnen eines neuen Unbestimmtheitswerts basiert auf dem alten Unbestimmtheitswert, dem gegenwärtigen Testsignalvertrauenswert und dem Maß internen Widerspruchs,

   ein Mittel zum Normalisieren des totalen Zustimungswerts für jede Schlußfolgerung basiert auf einer alten totalen Ablehnung und dem gegenwärtigen Testsignalablehnungswert,

   ein Mittel zum Berechnen der gegenwärtigen Plausibilität für jede Schlußfolgerung basiert auf der gegenwärtigen totalen Ablehnung und der Anzahl ausgewerteter Testsignale und

   ein Mittel zum Auswählen des gegenwärtigen Satzes Kandidatensignale basiert auf der gegenwärtigen totalen Zustimmung (auch vorher) und der Plausibilität für jede Schlußfolgerung.

9. Vorrichtung nach Anspruch 2, wobei die Ausgangsgewichte der Eingangs- (111 bis 114) und mittleren (121 bis 124) Knoten Werte haben, die durch Training eines rückwärts verzweigten neuronalen Netzwerks ermittelt worden sind, das die gleiche Architektur hat wie das neuronale Netzwerk, das empirische Bestimmtheits- und Unbestimmheitssignal-Trainingsdaten, die beim Testen realer Systeme ermittelt wurden, sowie Schlußfolgerungen verwendet, die von mindestens einem Experten bezüglich der Hinlänglichkeit der von den Kombinationen repräsentierten Information hergeleitet sind, um eine Diagnose für ein spezifisches zu testendes System abzugeben.

10. Die Vorrichtung nach Anspruch 9, wobei die Ausgangsgewichte der Eingangs- (111 bis 114) und mittleren (121 bis 124) Knoten generische Werte haben, di durch Training eines rückwärts v rzweigten neuronalen Netzwerks bestimmt worden sind, das dieselbe Architektur hat wie das neuronale Netzwerk, das normalisiert , zufällig generi rt Bestimmtheits- und Unbestimmheitssignal-Trainingsdaten verwendet sowie Schlußfolgerung n, die von mindestens einem Experten bezüglich der Hinlänglichkeit der von den Kombinationen repräsentierten Information hergeleit t worden sind, um eine Diagnos für System im allgemeinen abzugeben.

11. Die Vorrichtung nach Anspruch 5, wobei die Werte der Bestimmth its- und Unbestimmtheitssignale mit Wahrscheinlichkeitswerten korrespondieren.

12. Di Vorrichtung nach Anspruch 11, wobei die Trainingsdaten erste, zweite und dritte unzweideutige Kombinationen aufweisen, in denen die Datenhinlänglichkeitsfestlegung offensichtlich ist, wobei die erste unzweideutige Kombination das erste Bestimmtheitssignal aufweist, das einen Wert hat, der mit 100% Wahrscheinlichkeit korrespondiert, sowie das zweite Bestimmtheitssignal und das Unbestimmtheitssignal aufweist, die Nullwerte haben, und wobei die zweite unzweideutige Kombination das erste Bestimmtheitssignal und das Unbestimmtheitssignal aufweist, von denen jedes einen Wert hat, der mit 100% Wahrscheinlichkeit korrespondiert, sowie das zweite Bestimmtheitssignal aufweist, das einen Nullwert hat, und wobei die dritte unzweideutige Kombination beide Bestimmtheitssignale aufweist, die mit einheitlichen Wahrscheinlichkeiten korrespondieren, sowie das Unbestimmtheitssignal aufweist, das einen Nullwert hat.

13. Die Vorrichtung nach Anspruch 12, wobei die Trainingsdaten zwei Datensätze aufweist, von denen jeder eine vorbestimmte Anzahl zweideutiger Kombinationen hat, wobei:

beide Datensätze Bestimmtheitssignalwerte innerhalb eines geschlossenen Intervalls [0,1] haben, die entsprechend einer logarithmischen Normalverteilung zufällig generiert sind,

ein erster der Datensätze Unbestimmtheitssignalwerte hat, die entsprechend einer logarithmischen Normalverteilung zufällig generiert sind,

ein zweiter der Datensätze Unbestimmtheitssignalwerte hat, die zu Null gesetzt sind,

die so generierten Werte durch Normalisierung der Bestimmtheitssignalwerte in jeder zweideutigen Kombination eingestellt sind als Summe $(1 - S_U)$ zu ergeben, wobei alle normalisierten Bestimmtheitssignalwerte und die Unbestimmtheitssignalwerte, welche kleiner oder gleich einem vorbestimmten Wert sind, der auf der Anzahl der Elemente im System basiert, zu Null gesetzt sind, und dann die resultierenden Bestimmtheits- und Unbestimmtheitssignalwerte in jeder der zweideutigen Kombinationen normalisiert sind, um als Summe den Wert eins zu ergeben, und

der größere der resultierenden normalisierten Bestimmtheitssignalwerte als der erste Bestimmtheitssignalwert in jeder der zweideutigen Kombinationen bezeichnet wird, in der die Bestimmtheitssignalwerte ungleich sind.

14. Die Vorrichtung nach Anspruch 11, wobei

die Summe der gewichteten, jedem der mittleren Knoten eingegebenen Ausgänge und der Ausgangsmodus im jeweiligen Knoten mit einer sigmoidalen Aktivierungsfunktion verarbeitet werden,

die Gewichte der ersten, zweiten und dritten Ausgänge des ersten Eingangsknotens jeweils (-9,640), 5,049 und (-1,624) betragen,

die Gewichte des ersten, zweiten und dritten Ausgangs des zweiten Eingangsknotens jeweils 15,641, (-8,491) und 2,436 betragen,

die Gewichte des ersten, zweiten und dritten Ausgangs des dritten Eingangsknotens jeweils (-6,680), 3,627 und (-1,237) betragen,

die Gewichte des ersten, zweiten und dritten Ausgangs des vierten Eingangsknotens jeweils (-0,422), 0,442 und (-0,427) betragen,

das Gewicht des Ausgangs des ersten mittleren Knotens (-19,214) beträgt,

das Gewicht des Ausgangs des zweiten mittleren Knotens 11,457 beträgt,

das Gewicht des Ausgangs des dritt n mittleren Knotens (-2,483) beträgt und

das Gewicht des Ausgangs des vierten mittleren Knotens 4,081 beträgt.

15. Die Vorrichtung nach Anspruch 14, wobei die Aktivierungsfunktion logistisch ist.

16. Die Vorrichtung nach Anspruch 15, wobei die Aktivierungsfunktion $1/(1\text{-}e_{-x})$ lautet, mit x als ungewichtetem Ausgang eines gegeb n n Knotens.

17. Ein diagnostischer Tester zum Abg ben einer Diagnose auf Basis der Lokalisation und Isolation versagter Systemelemente eines Syst ms mit einer definierten Anzahl funktionaler Elemente, wobei der Tester die Vorrichtung nach jedem beliebigen der vorhergehenden Ansprüche aufweist sowie Eingangsmittel (13, 26, 34, 42 52) zum Liefern von Testsignalen an das Auswertungsmittel.

18. Der diagnostische Tester nach Anspruch 17, wobei das Eingangsmittel operatoraktivierte Eingangsmittel (10, 26) zum Eingeben von Testdaten aufweist, die sich auf mindestens einen vorbestimmten Aspekt des Systems beziehen, sowie zum Generieren von Testsignalen, die mit den Testdaten korrespondieren.

19. Der diagnostische Tester nach Anspruch 17, wobei das Eingangsmittel ein automatisches Testmittel (34) aufweist, das zum Durchführen ausgewählter Tests auf dem System und zum Generieren von Testsignalen, die mit den Testergebnissen korrespondieren, sensibel für ein Kontrollsignal ist.

20. Der diagnostische Tester nach Anspruch 19, zusätzlich mit:
einem Kontrollmittel (32), das zum Produzieren des Kontrollsignals sensibel für das Ausgangssignal ist, um das Kontrollsignal zu produzieren, um zu erwirken, daß das automatische Testmittel mindestens einen weiteren ausgewählten Test aus dem System durchführt, wenn das Ausgangssignal anzeigt, daß nicht hinlänglich viele Testdaten ausgewertet worden sind, sowie um ein Schlußfolgerungssignal zu produzieren, das in Übereinstimmung mit dem ersten Kandidatensignal eine Diagnose anzeigt, wenn das Ausgangssignal anzeigt, daß hinlänglich viele Testdaten aufgewertet worden sind.

21. Der diagnostische Tester nach Anspruch 20, wobei das Kontrollmittel (32) das Kontrollsignal zum Auswählen des mindestens einen weiteren ausgewählten Tests in Übereinstimmung mit mindestens einer vorhergehenden Auswertung der Testsignale produziert.

22. Der diagnostische Tester nach Anspruch 17 zusätzlich mit:

einer Anzeige (12, 22, 36) und

einem Mittel (24), das sensibel für das Ausgangssignal ist, um die Anzeige zu steuern, die Notwendigkeit zusätzlicher Testdaten anzuzeigen, und um das Eingangsmittel zu steuern, mindestens ein weiteres Testsignal zur Auswertung durch das Auswertungsmittel zu akzeptieren, wenn das Ausgangssignal anzeigt, daß nicht hinlänglich viele Testdaten ausgewertet worden sind, und um die für das erste Kandidatensignal sensible Anzeige zu steuern, eine Diagnose anzuzeigen, wenn das Ausgangssignal anzeigt, daß hinlänglich viele Testdaten ausgewertet worden sind.

23. Ein diagnostischer Tester nach einem der Ansprüche 17 bis 22 und/oder mit einer Vorrichtung nach einem der Ansprüche 1 bis 16, wobei der Tester eine Anordnung zum Testen eines Systems entsprechend einem Satz definierter Beziehungen zwischen einer Anzahl von Quellen zum Versorgen mit Informationen über das System und einer Anzahl von Schlußfolgerungen über die Natur oder den Zustand des Systems aufweist, sowie:

ein erstes Mittel (34) zum fortfolgenden Auswählen (551) einer Informationsquelle unter der Anzahl der Informationsquellen zur Abfrage entsprechend der relativen Menge an Informationen, die von jeder Informationsquelle geliefert ist, bis alle Informationsquellen ausgewählt worden sind oder die Information, die dadurch geliefert würde, bestimmt worden ist,

ein zweites Mittel (34) zum fortfolgenden weiteren Auswählen einer Informationsquelle aus einer Anzahl von Informationsquellen zum Abfragen entsprechend dem Kriterium, welche Informationsquelle den Bestimmtheitsgrad ansteigen läßt, daß in ausgewählte Schlußfolgerung zu einem Kandidaten eine gültige Diagnose des getesteten Systems bildet.

24. Der diagnostische Tester nach Anspruch 23, wobei das zweite Auswahlmittel folgendes aufweist:

ein Mittel zum Zuw isen eines Vertrauenswerts zur Information, die von ein r Informationsquelle geliefert ist,

ein Mittel, das sensibel ist für die Vertrauenswerte und für die Information, di von abgefragten Informationsqu llen geli f rt ist, um einen Bestimmth itsgrad für jede der Schlußfolgerungen zu berechn n, daß er eine gültige Diagnose bildet,

ein Mittel zum Auswählen von Schlußfolgerungen zu einem Kandidaten entsprechend den relativen Werten der berechneten Bestimmtheitsgrade für jede Schlußfolgerung.

25. Der diagnostische Tester nach Anspruch 24 zusätzlich mit:
einem ersten Mittel zum Identifizieren, ob mehr als eine Schlußfolgerung zu einem Kandidaten ausgewählt worden ist, welche Informationsquellen, wenn überhaupt eine, von einer der beiden Schlußfolgerungen zum Kandidaten mit den dann höchsten Bestimmtheitsgraden abhängen und nicht von der anderen, und, wenn mehr als eine solche Informationsquelle identifiziert ist, zum Identifizieren, welche der Informationsquellen die meiste Information gewährt über die Zustimmung der Schlußfolgerung zum Kandidaten, von der sie abhängt.

26. Der diagnostische Tester nach Anspruch 25 zusätzlich mit:
einem zweiten Mittel, das sensibel ist für das erste Identifizierungsmittel, welches festlegt, daß keine Informationsquelle dem Identifikationskriterium des ersten Identifizierungsmittels genügt, und sensibel ist für das Auswahlmittel, das dann nur eine Schlußfolgerung zum Kandidaten ausgewählt hat, um die Informationsquelle, wenn es eine gibt, zu identifizieren, die die meiste Zustimmung für die Schlußfolgerung zum Kandidaten mit dem dann höchsten Bestimmtheitsgrad liefert, wenn dann mehr als eine Schlußfolgerung zum Kandidaten ausgewählt worden ist, oder für die eine Schlußfolgerung zum Kandidaten, wenn dann nur eine Schlußfolgerung zum Kandidaten ausgewählt worden ist.

27. Der diagnostische Tester nach Anspruch 26 zusätzlich mit:
einem dritten Mittel, das sensibel ist für das zweite Identifizierungsmittel, welches bestimmt, daß keine Informationsquelle dem Identifikationskriterium des zweiten Identifizierungsmittels zum Identifizieren der Informationsquelle, wenn es eine gibt, genügt, die die meisten von der Schlußfolgerung zum Kandidaten verschiedenen Schlußfolgerungen unterstützt, die dann den höchsten Bestimmtheitsgrad haben.

Revendications

1. Appareil automatique d'évaluation de données de test pour utilisation dans un appareil de test de diagnostic qui établit un diagnostic sur la base d'une localisation ou d'une isolation d'éléments de système défaillants d'un système ayant un nombre défini d'éléments fonctionnels, ledit appareil comprenant :

des moyens pour sélectionner le test suivant à effectuer sur le système à tester ;
des moyens pour générer les données de test correspondantes et pour les fournir au système à tester ;
des moyens pour détecter et recueillir des paramètres prédéterminés de fonctionnement du système ;
des moyens d'évaluation (54), sensibles à au moins un signal de test entré correspondant aux données de test S_T concernant au moins un paramètre prédéterminé du système, pour produire en utilisant une méthode de raisonnement évidentiel probabiliste :

des premier (S_{CP1}) et deuxième (S_{CP2}) signaux candidats correspondant respectivement à des premier et deuxième diagnostics possibles de l'état du système ayant respectivement les premier et deuxième plus hauts niveaux de certitude d'être valables, et
des premier (S_{P1}) et deuxième (S_{P2}) signaux de certitude correspondant respectivement à des valeurs desdits premier et deuxième plus hauts niveaux de certitude ; et

caractérisé par des moyens de suffisance des tests (56), sensibles auxdits premier et deuxième signaux de certitude, pour produire un signal de sortie (S_S) indiquant si assez de données de test ont été évaluées pour établir un diagnostic, lesdits moyens de suffisance des tests comprenant un réseau neuronal ayant un noeud de sortie (130') et au moins trois noeuds d'entrée (111', 112', 114') recevant respectivement lesdits premier et deuxième signaux de certitude et un signal de polarisation prédéterminé en tant qu'entrée, lesdits noeuds d'entrée ayant des sorties pondérées, les pondérations de sortie correspondant à un modèle de données d'expert mettant en corrélation des combinaisons de signaux de certitude avec au moins une opinion d' xpert concernant la capacité

d'établir un diagnostic sur la base de chaque combinaison de val urs de signaux de certitude.

2. Appareil s lon la revendication 1, dans l quel :

lesdits moyens d'évaluation produisent aussi un signal d'incertitude S_U correspondant à une mesure de l'incertitude qu'au moins un signal de test évalué p ut être évalué de façon valable ; t
ledit réseau neuronal comprend :

un ensemble (110) de premier (111), deuxième (112), troisième (113) et quatrième (114) noeuds d'entrée, chacun ayant des première, deuxième et troisième sorties pondérées par une pondération fixe prédéterminée, lesdits premier (111) et deuxième (112) noeuds d'entrée recevant respectivement lesdits premier (S_{P1}) et deuxième (S_{P2}) signaux de certitude en tant qu'entrée, ledit troisième (113) noeud d'entrée recevant ledit signal d'incertitude (S_U), et ledit quatrième noeud d'entrée (114) recevant ledit signal de polarisation prédéterminé (BIAS) ;
un ensemble (120) de premier (121), deuxième (122), troisième (123) et quatrième (124) noeuds intermédiaires, chacun ayant une sortie pondérée par une pondération fixe prédéterminée, et ledit premier noeud intermédiaire (121) recevant la somme des premières sorties pondérées desdits noeuds d'entrée en tant qu'entrée, ledit deuxième noeud intermédiaire (122) recevant celle des deuxièmes sorties pondérées desdits noeuds d'entrée en tant qu'entrée, ledit troisième noeud intermédiaire (123) recevant la somme des troisièmes sorties pondérées desdits noeuds d'entrée en tant qu'entrée, et ledit quatrième noeud intermédiaire (124) recevant ledit signal de polarisation (BIAS) prédéterminé ; et
un noeud de sortie (130), sensible à la somme desdites sorties pondérées desdits noeuds intermédiaires, pour produire ledit signal de sortie (S_S), les pondérations de sortie desdits noeuds d'entrée et intermédiaires correspondant à un modèle de données d'expert mettant en corrélation des combinaisons de valeurs de signaux de certitude et d'incertitude avec au moins une opinion d'expert concernant la capacité d'établir un diagnostic sur la base de chaque combinaison de valeurs de signaux de certitude et d'incertitude, lesdits moyens de suffisance des tests évaluant ainsi aussi ledit signal d'incertitude pour produire ledit signal de sortie.

3. Appareil selon la revendication 2, dans lequel :

lesdits moyens d'évaluation produisent aussi un signal S_N correspondant à une mesure du niveau de certitude qu'un diagnostic ne correspondant pas auxdits premier ou deuxième signaux candidats ni audit signal d'incertitude est un diagnostic valable ; et
lesdits moyens de suffisance des tests évaluent aussi ledit signal S_N pour produire ledit signal de sortie.

4. Appareil selon la revendication 2, dans lequel lesdits moyens d'évaluation (54) comprennent :

des moyens pour stocker un modèle de relations prédéterminées de flux d'information dans le système soumis au test ;
des moyens pour associer lesdits signaux de test à des ensembles de causes possibles conformément audit modèle, et pour déterminer les intersections desdits ensembles de causes possibles pour des combinaisons de signaux de test, lesdits signaux candidats étant dérivés à partir desdites intersections ; et
des moyens pour déterminer pour chaque signal candidat une mesure du niveau de certitude qu'il représente un diagnostic valable.

5. Appareil selon la revendication 4, dans lequel lesdits moyens d'évaluation (54) comprennent des moyens pour déterminer jusqu'à quel degré un conflit existe entre ledit au moins un premier signal candidat et ledit au moins un signal de test indiquant le niveau de certitude qu'un résultat non anticipé (UR) a été obtenu, ledit signal d'incertitude ayant une valeur correspondant audit niveau UR de certitude.

6. Appareil selon la revendication 1, dans lequel les valeurs desdits premier et deuxième plus hauts niveaux de certitude sont des valeurs de probabilité.

7. Appareil selon la r vendication 2, dans lequel ladite mesure d'incertitude a une valeur de probabilité.

8. Appareil selon la revendication 5, dans lequel lesdits moyens de détermination d'UR comprennent :

des moyens pour définir une pluralité de conclusions correspondant à des diagnostics possibles du système ;
des moyens pour affecter une valeur de confiance à chaque signal de test successivement entré ;
des moy ns pour calculer la confirmation et l r jet pour chaqu conclusion basée sur ladite valeur d confiance du signal de test actuellement entré ;
des moyens pour déterminer si le signal de test actuellement entré est en conflit avec un ensemble, sélectionné à ce moment-là, desdites conclusions corr spondant aux signaux candidats ;
des moyens pour obtenir une mesure de conflit interne basée sur des valeurs cumulées de confirmation totale et les valeurs de confirmation du signal de test actuel pour toutes lesdites conclusions ;
des moyens pour calculer la présente valeur dudit signal d'incertitude basée sur le nombre de signaux de test évalués, si le présent signal de test n'est pas un conflit ; et, basée sur le nombre de signaux de test évalués et sur le nombre de conflits, si le présent signal de test est un conflit ;
des moyens pour calculer une nouvelle valeur de confirmation totale pour chaque conclusion basée sur l'ancienne valeur de confirmation totale, la valeur de confirmation et la valeur de confiance du présent signal de test, une ancienne valeur d'incertitude, et ladite mesure de conflit interne ;
des moyens pour calculer une nouvelle valeur d'incertitude basée sur l'ancienne valeur d'incertitude, la valeur de confiance du présent signal de test et ladite mesure de conflit interne ;
des moyens pour normaliser la valeur de confirmation totale pour chaque conclusion en fonction de l'ancienne valeur de confirmation totale, et de la valeur du présent signal d'incertitude ;
des moyens pour calculer un nouveau rejet total pour chaque conclusion en fonction d'un ancien rejet total et de la valeur de rejet du présent signal de test ;
des moyens pour calculer la présente vraisemblance pour chaque conclusion basée sur le présent rejet total et le nombre de signaux de test évalués ;
des moyens pour sélectionner l'ensemble actuel de signaux candidats en fonction de la présente confirmation totale et de la vraisemblance pour chaque conclusion.

9. Appareil selon la revendication 2, dans lequel lesdites pondérations de sortie desdits noeuds d'entrée (111-114) et intermédiaires (121-124) ont des valeurs obtenues par apprentissage d'un réseau neuronal à propagation en retour, ayant la même architecture que ledit réseau neuronal, en utilisant des données d'apprentissage de signaux de certitude et d'incertitude empiriques obtenues par des tests sur des systèmes réels, et des conclusions dérivées d'au moins un expert concernant la suffisance des informations représentées par lesdites combinaisons pour établir un diagnostic pour un système spécifique à tester.

10. Appareil selon la revendication 9, dans lequel lesdites pondérations de sortie desdits noeuds d'entrée (111-114) et intermédiaires (121-124) ont des valeurs génériques obtenues par apprentissage d'un réseau neuronal à propagation en retour, ayant la même architecture que ledit réseau neuronal, en utilisant des données d'apprentissage normalisées pour le signal de certitude et d'incertitude générées de manière aléatoire, et des conclusions dérivées d'au moins un expert concernant la suffisance des informations représentées par lesdites combinaisons pour établir un diagnostic pour des systèmes en général.

11. Appareil selon la revendication 5, dans lequel les valeurs desdits signaux de certitude et d'incertitude correspondent à des valeurs de probabilité.

12. Appareil selon la revendication 11, dans lequel lesdites données d'apprentissage incluent des première, deuxième et troisième combinaisons sans ambiguïté dans lesquelles la détermination de la suffisance des données est évidente, ladite première combinaison sans ambiguïté comprenant ledit premier signal de certitude ayant une valeur correspondant à une probabilité de 100 %, et ledit deuxième signal de certitude et ledit signal d'incertitude ayant des valeurs de zéro, ladite deuxième combinaison sans ambiguïté comprenant ledit premier signal de certitude et ledit signal d'incertitude, chacun ayant une valeur correspondant à une probabilité de 100 %, et ledit deuxième signal de certitude ayant une valeur de zéro, et ladite troisième combinaison sans ambiguïté comprenant les deux signaux de certitude ayant des valeurs correspondant à des probabilités uniformes et ledit signal d'incertitude ayant une valeur de zéro.

13. Appareil selon la revendication 12, dans lequel lesdites données d'apprentissage incluent deux ensembles de données, chacun ayant un nombre prédéterminé de combinaisons ambiguës où :

les deux ensembles de donné s ont des valeurs de signaux de certitude dans un intervalle f rmé [0,1] générées au hasard selon une distribution log-normale ;
un premier desdits ensembles de données a des valeurs de signaux d'incertitude générées au hasard selon

une distribution log-normale ;
un deuxième desdits ensembles de données a des valeurs de signaux d'incertitude établies à zéro ;
les valeurs ainsi générées sont ajusté s en normalisant les valeurs de signaux de certitude dans chaque combinaison ambiguë pour totaliser ($1-S_U$), toutes les valeurs normalisées de signaux de certitude et les valeurs de signaux d'incertitude inféri ures ou égales à un valeur prédéterminée basée sur le nombre d'éléments dans le système sont établies à zéro ; et alors les valeurs résultantes des signaux de certitude t d'incertitude dans chacune des combinaisons ambiguës sont normalisées pour totaliser la valeur un ; et
la plus grande des valeurs normalisées résultantes des signaux de certitude est désignée comme la première valeur de signaux de certitude dans chacune desdites combinaisons ambiguës dans lesquelles les valeurs de signaux de certitude sont inégales.

14. Appareil selon la revendication 11, dans lequel :

la somme des sorties pondérées entrées à chacun des noeuds intermédiaires et au noeud de sortie est traitée dans le noeud respectif par une fonction d'activation sigmoïde ;
les pondérations des première, deuxième et troisième sorties du premier noeud d'entrée sont (-9,640), 5,049, et (-1,624), respectivement ;
les pondérations des première, deuxième et troisième sorties du deuxième noeud d'entrée sont 15,641, (-8,491), et 2,436, respectivement ;
les pondérations des première, deuxième et troisième sorties du troisième noeud d'entrée sont (-6,680), 3,627, et (-1,237), respectivement ;
les pondérations des première, deuxième et troisième sorties du quatrième noeud d'entrée sont (-0,422), 0,442, et (-0,427), respectivement ;
la pondération de la sortie du premier noeud intermédiaire est (-19,214) ;
la pondération de la sortie du deuxième noeud intermédiaire est 11,457 ;
la pondération de la sortie du troisième noeud intermédiaire est (-2,483) ; et
la pondération de la sortie du quatrième noeud intermédiaire est 4,081.

15. Appareil selon la revendication 14, dans lequel ladite fonction d'activation est logistique.

16. Appareil selon la revendication 15, dans lequel ladite fonction d'activation est $1/(1+e^{-x})$, où x est la sortie non pondérée d'un noeud donné.

17. Appareil de test de diagnostic pour établir un diagnostic sur la base d'une localisation et isolation de composants de système défaillants d'un système ayant un nombre défini d'éléments fonctionnels, l'appareil de test comprenant l'appareil selon l'une quelconque des revendications précédentes, l'appareil de test comprenant en outre des moyens d'entrée (13, 26, 34, 42, 52) pour fournir des signaux de test auxdits moyens d'évaluation.

18. Appareil de test de diagnostic selon la revendication 17, dans lequel lesdits moyens d'entrée comprennent des moyens d'entrée (13, 26) actionnés par l'opérateur pour entrer des données de test concernant au moins un aspect prédéterminé du système, et pour générer des signaux de test correspondant aux données de test.

19. Appareil de test de diagnostic selon la revendication 17, dans lequel lesdits moyens d'entrée comprennent des moyens de test automatiques (34) sensibles à un signal de commande pour effectuer des tests sélectionnés sur le système, et pour générer des signaux de test correspondant aux résultats de test.

20. Appareil de test de diagnostic selon la revendication 19, comprenant en outre :
des moyens de commande (32) sensibles audit signal de sortie pour produire ledit signal de commande pour amener lesdits moyens de test automatiques à effectuer au moins un autre test sélectionné sur le système si ledit signal de sortie indique que des données de test insuffisantes ont été évaluées ; et pour produire un signal de conclusion indiquant un diagnostic conformément audit premier signal candidat si ledit signal de sortie indique que des données de test suffisantes ont été évaluées.

21. Appareil de test de diagnostic selon la revendication 20, dans lequel lesdits moyens de command (32) produisent ledit signal de commande pour sélectionner ledit au moins un autre test sélectionné conformément à au moins une évaluation antérieur des signaux de test.

22. Appareil de test de diagnostic selon la rev ndication 17, comprenant n outre :

un affichage (12, 22, 36) ; et
des moyens (24) sensibles audit signal de sortie pour commander ledit affichage pour indiquer le besoin pour des données de t st supplémentaires et pour commander lesdits moyens d'entrée de façon à accepter au moins un autre signal de test à évaluer par lesdits moyens d'évaluation si ledit signal d sortie indique qu des données de test insuffisantes ont été évaluées ; et pour commander ledit affichage sensible audit premier signal candidat de façon à indiquer un diagnostic si l dit signal de sortie indique que des données de test suffisantes ont été évaluées.

23. Appareil de test de diagnostic selon l'une quelconque des revendications 17 à 22, et/ou comprenant un appareil selon l'une quelconque des revendications 1 à 16, l'appareil de test comprenant un agencement pour tester un système selon un ensemble de relations définies entre une pluralité de sources pour fournir des informations concernant le système et une pluralité de conclusions concernant la nature ou l'état du système, ledit appareil de test comprenant :

des premiers moyens (34) pour sélectionner successivement (551) une source d'informations parmi la pluralité de sources d'informations pour l'interroger selon la quantité d'information relative fournie par chaque source d'informations jusqu'à ce que toutes les sources d'informations aient été sélectionnées ou que les informations qui seraient fournies par celles-ci aient été déterminées ;
des deuxièmes moyens (34) pour sélectionner encore une fois successivement une source d'informations parmi la pluralité de sources d'informations pour l'interroger selon la source d'informations qui augmentera le niveau de certitude qu'une conclusion candidate choisie constitue un diagnostic valable du système testé.

24. Appareil de test de diagnostic selon la revendication 23, dans lequel lesdits deuxièmes moyens de sélection comprennent :

des moyens pour affecter une valeur de confiance aux informations fournies par une source d'informations ;
des moyens sensibles auxdites valeurs de confiance et aux informations fournies par des sources d'informations interrogées pour calculer un niveau de certitude pour chacune des conclusions qu'elle constitue un diagnostic valable ;
des moyens pour sélectionner des conclusions candidates selon les valeurs relatives des niveaux de certitude calculés pour chaque conclusion.

25. Appareil de test de diagnostic selon la revendication 24 comprenant en outre :
des premiers moyens pour identifier, si plus d'une conclusion candidate a été sélectionnée, quelles sources d'informations, le cas échéant, dépendent d'une des deux conclusions candidates avec alors les plus hauts niveaux de certitude et pas de l'autre, et, si plus d'une telle source d'informations est identifiée, pour identifier laquelle de ces sources d'informations fournit le plus d'information concernant la confirmation pour la conclusion candidate dont elle dépend.

26. Appareil de test de diagnostic selon la revendication 25 comprenant en outre :
des deuxièmes moyens, sensibles auxdits premiers moyens d'identification déterminant qu'aucune source d'informations ne satisfait aux critères d'identification desdits premiers moyens d'identification, et sensibles auxdits moyens de sélection ayant alors sélectionné seulement une conclusion candidate, pour identifier la source d'informations, le cas échéant, qui fournit le plus de confirmation pour la conclusion candidate ayant alors le plus haut niveau de certitude, si plus d'une conclusion candidate a alors été sélectionnée, ou pour la conclusion candidate, si seulement une conclusion candidate a alors été sélectionnée.

27. Appareil de test de diagnostic selon la revendication 26 comprenant en outre :
des troisièmes moyens, sensibles auxdits deuxièmes moyens d'identification déterminant qu'aucune source d'informations ne satisfait aux critères d'identification desdits deuxièmes moyens d'identification, pour identifier la source d'informations, le cas échéant, qui confirme le plus grand nombre de conclusions autres que la conclusion candidate ayant alors le plus haut niveau de certitude.

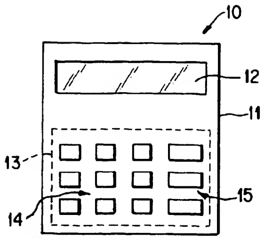

FIG. 1

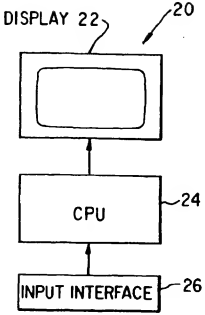

FIG.4

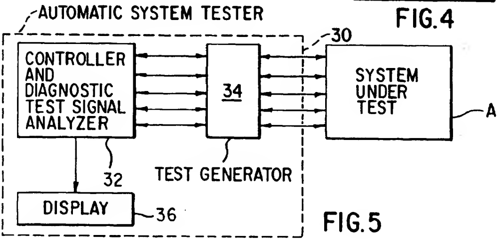

FIG.5

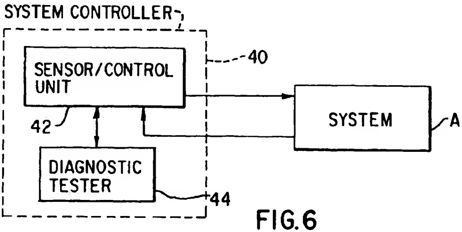

FIG.6

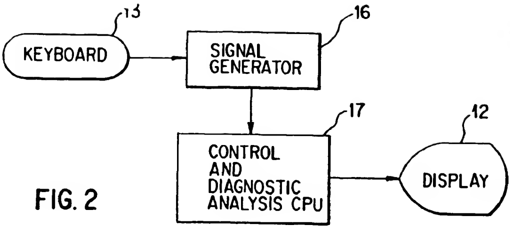

FIG. 2

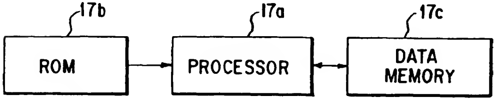

FIG. 3

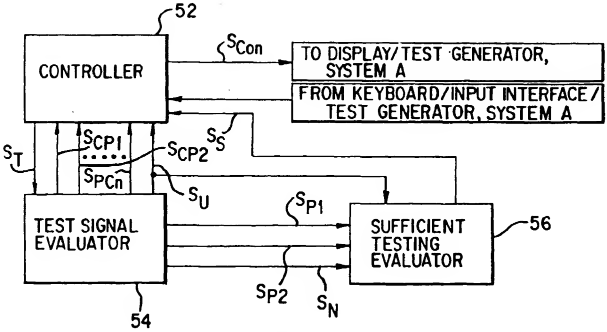

FIG.7

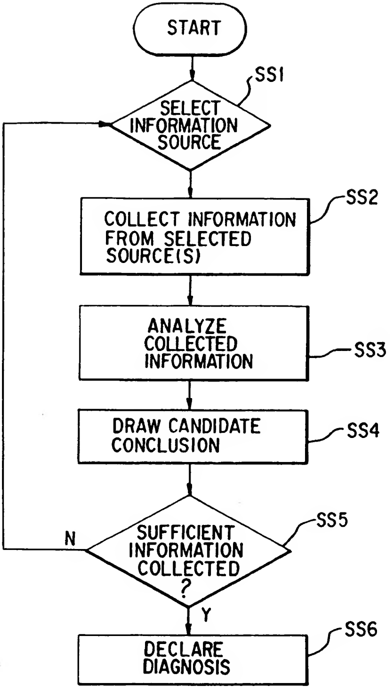
START
SELECT INFORMATION SOURCE
SS1
COLLECT INFORMATION FROM SELECTED SOURCE(S)
SS2
ANALYZE COLLECTED INFORMATION
SS3
DRAW CANDIDATE CONCLUSION
SS4
SUFFICIENT INFORMATION COLLECTED ?
SS5
N
Y
DECLARE DIAGNOSIS
SS6

FIG. 8

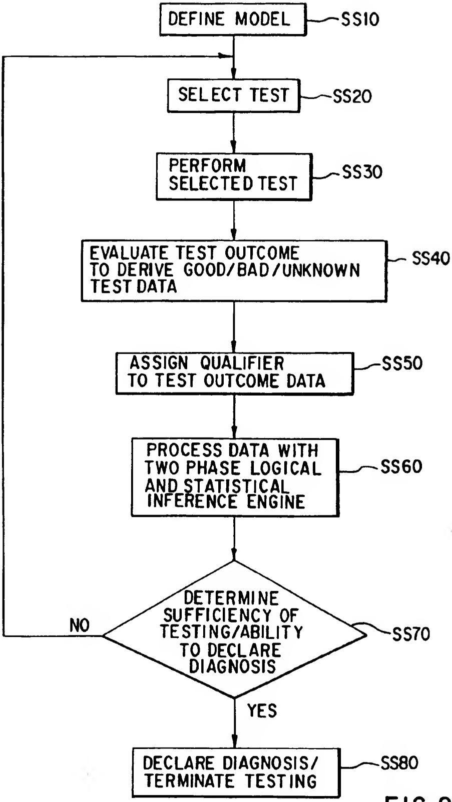
DEFINE MODEL
SS10
SELECT TEST
SS20
PERFORM SELECTED TEST
SS30
EVALUATE TEST OUTCOME TO DERIVE GOOD/BAD/UNKNOWN TEST DATA
SS40
ASSIGN QUALIFIER TO TEST OUTCOME DATA
SS50
PROCESS DATA WITH TWO PHASE LOGICAL AND STATISTICAL INFERENCE ENGINE
SS60
DETERMINE SUFFICIENCY OF TESTING/ABILITY TO DECLARE DIAGNOSIS
SS70
NO
YES
DECLARE DIAGNOSIS/ TERMINATE TESTING
SS80

FIG. 9

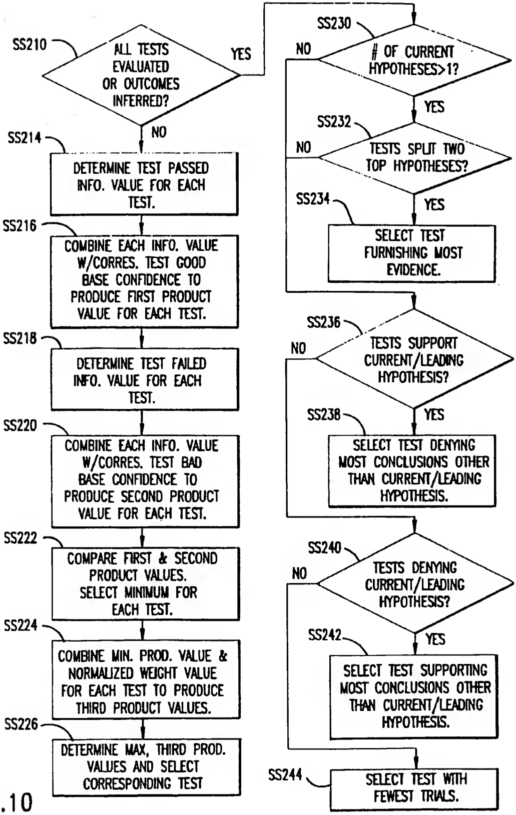
SS210
ALL TESTS EVALUATED OR OUTCOMES INFERRED?
YES
NO
SS214
DETERMINE TEST PASSED INFO. VALUE FOR EACH TEST.
SS216
COMBINE EACH INFO. VALUE W/CORRES. TEST GOOD BASE CONFIDENCE TO PRODUCE FIRST PRODUCT VALUE FOR EACH TEST.
SS218
DETERMINE TEST FAILED INFO. VALUE FOR EACH TEST.
SS220
COMBINE EACH INFO. VALUE W/CORRES. TEST BAD BASE CONFIDENCE TO PRODUCE SECOND PRODUCT VALUE FOR EACH TEST.
SS222
COMPARE FIRST & SECOND PRODUCT VALUES. SELECT MINIMUM FOR EACH TEST.
SS224
COMBINE MIN. PROD. VALUE & NORMALIZED WEIGHT VALUE FOR EACH TEST TO PRODUCE THIRD PRODUCT VALUES.
SS226
DETERMINE MAX, THIRD PROD. VALUES AND SELECT CORRESPONDING TEST
SS230
OF CURRENT HYPOTHESES>1?
NO
YES
SS232
TESTS SPLIT TWO TOP HYPOTHESES?
NO
YES
SS234
SELECT TEST FURNISHING MOST EVIDENCE.
SS236
TESTS SUPPORT CURRENT/LEADING HYPOTHESIS?
NO
YES
SS238
SELECT TEST DENYING MOST CONCLUSIONS OTHER THAN CURRENT/LEADING HYPOTHESIS.
SS240
TESTS DENYING CURRENT/LEADING HYPOTHESIS?
NO
YES
SS242
SELECT TEST SUPPORTING MOST CONCLUSIONS OTHER THAN CURRENT/LEADING HYPOTHESIS.
SS244
SELECT TEST WITH FEWEST TRIALS.

FIG.10

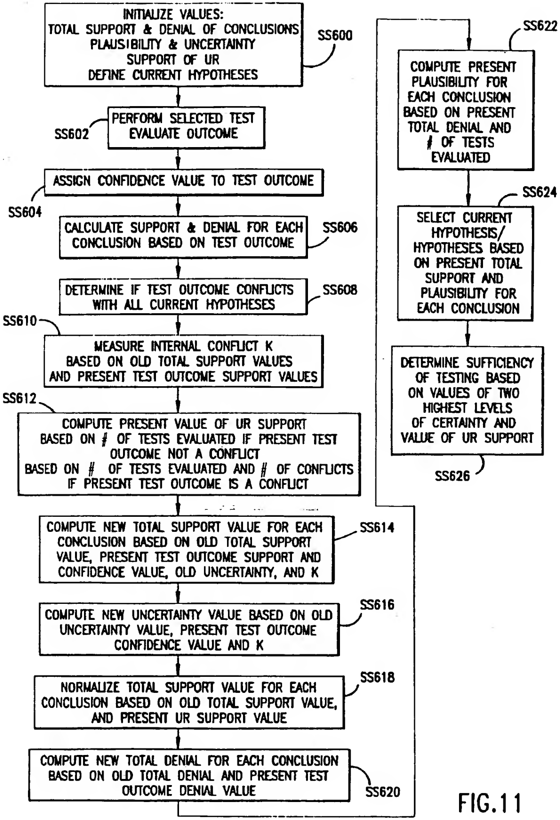
INITIALIZE VALUES:
TOTAL SUPPORT & DENIAL OF CONCLUSIONS
PLAUSIBILITY & UNCERTAINTY
SUPPORT OF UR
DEFINE CURRENT HYPOTHESES
SS600
PERFORM SELECTED TEST
EVALUATE OUTCOME
SS602
ASSIGN CONFIDENCE VALUE TO TEST OUTCOME
SS604
CALCULATE SUPPORT & DENIAL FOR EACH CONCLUSION BASED ON TEST OUTCOME
SS606
DETERMINE IF TEST OUTCOME CONFLICTS WITH ALL CURRENT HYPOTHESES
SS608
SS610
MEASURE INTERNAL CONFLICT K BASED ON OLD TOTAL SUPPORT VALUES AND PRESENT TEST OUTCOME SUPPORT VALUES
SS612
COMPUTE PRESENT VALUE OF UR SUPPORT
BASED ON # OF TESTS EVALUATED IF PRESENT TEST OUTCOME NOT A CONFLICT
BASED ON # OF TESTS EVALUATED AND # OF CONFLICTS IF PRESENT TEST OUTCOME IS A CONFLICT
COMPUTE NEW TOTAL SUPPORT VALUE FOR EACH CONCLUSION BASED ON OLD TOTAL SUPPORT VALUE, PRESENT TEST OUTCOME SUPPORT AND CONFIDENCE VALUE, OLD UNCERTAINTY, AND K
SS614
COMPUTE NEW UNCERTAINTY VALUE BASED ON OLD UNCERTAINTY VALUE, PRESENT TEST OUTCOME CONFIDENCE VALUE AND K
SS616
NORMALIZE TOTAL SUPPORT VALUE FOR EACH CONCLUSION BASED ON OLD TOTAL SUPPORT VALUE, AND PRESENT UR SUPPORT VALUE
SS618
COMPUTE NEW TOTAL DENIAL FOR EACH CONCLUSION BASED ON OLD TOTAL DENIAL AND PRESENT TEST OUTCOME DENIAL VALUE
SS620
SS622
COMPUTE PRESENT PLAUSIBILITY FOR EACH CONCLUSION BASED ON PRESENT TOTAL DENIAL AND # OF TESTS EVALUATED
SS624
SELECT CURRENT HYPOTHESIS/ HYPOTHESES BASED ON PRESENT TOTAL SUPPORT AND PLAUSIBILITY FOR EACH CONCLUSION
DETERMINE SUFFICIENCY OF TESTING BASED ON VALUES OF TWO HIGHEST LEVELS OF CERTAINTY AND VALUE OF UR SUPPORT
SS626

FIG.11

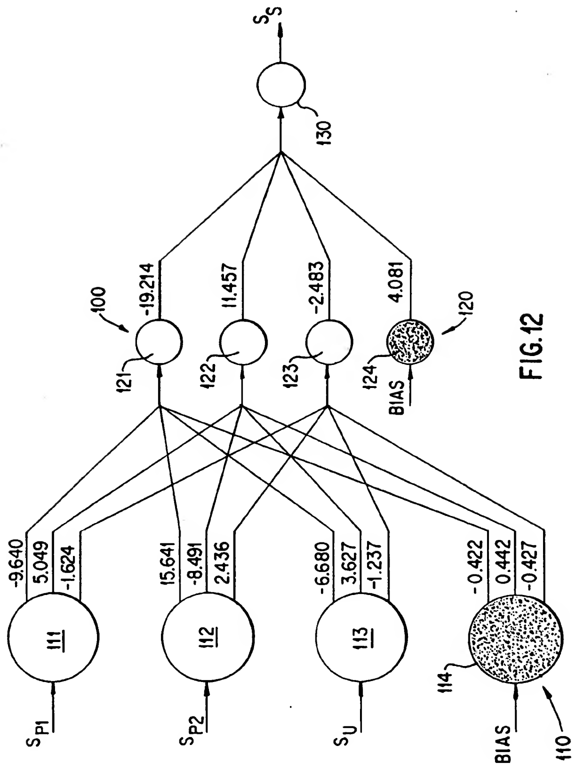
S_S
130
100
-19.214
11.457
-2.483
4.081
120
121
122
123
124
BIAS
-9.640
5.049
-1.624
15.641
-8.491
2.436
-6.680
3.627
-1.237
-0.422
0.442
-0.427
111
112
113
114
S_{P1}
S_{P2}
S_U
BIAS
110

FIG.12

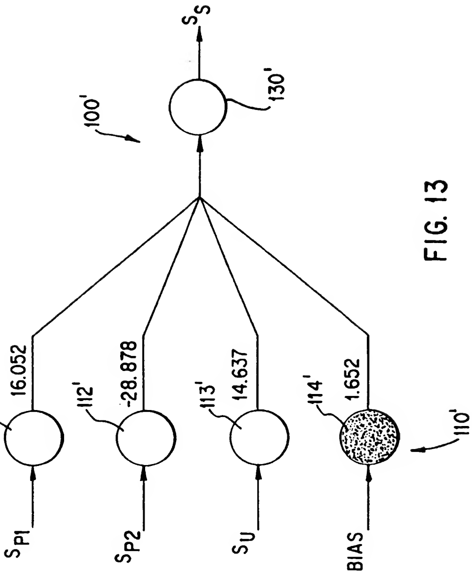
S_S
130'
100'
111'
16.052
112'
-28.878
113'
14.637
114'
1.652
110'
S_{P1}
S_{P2}
S_U
BIAS

FIG. 13